Quantifying the Impact of Change Orders on Construction Labor Productivity Using System Dynamics

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A Thesis
In the Department
of
Building, Civil and Environmental Engineering

Presented in Partial Fulfillment of the Requirements
For the Degree of
Doctor of Philosophy (Building Engineering) at
Concordia University
Montreal, Quebec, Canada

September 2019

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Concordia University

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Doctor of Philosophy (Building Engineering)

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ABSTRACT

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Researchers and industry practitioners agree that changes are unavoidable in construction projects and may become troublesome if poorly managed. One of the root causes of sub-optimal productivity in construction projects is the number and impact of changes introduced to the initial scope of work during the course of project execution. In labor-intensive construction projects, labor costs represent a substantial percentage of the total project budget. Understanding labor productivity is essential to project success. If productivity is impacted by any reasons such as extensive changes or poor managerial policies, labor costs will increase over and above planned cost. The true challenge of change management is having a comprehensive understanding of change impacts and how these impacts can be reduced or prevented before they cascade forming serious problems. This thesis proposes a change management framework that project teams can use to quantify labor productivity losses due to change orders and managerial policies across all phases of construction projects. The proposed framework has three models; fuzzy risk-based change management, AI baseline-productivity estimating, and system dynamics to illustrate cause-impact relationships. These models were developed in five stages.

In the first stage, the fuzzy risk-based change management (FRCM) model was developed to prioritize change orders in a way that only essential change orders can be targeted. In this stage, Fuzzy Analytic Hierarchy Process (F-AHP) and Hierarchical Fuzzy Inference System are

utilized to calculate relative weights of the factors considered and generate a score for each contemplated change. In the second stage, baseline productivity model was developed considering a set of environmental and operational variables. In this step, various techniques were used including Stepwise, Best Subset, Evolutionary Polynomial Regression (EPR), General Regression Neural Network (GRNN), Artificial Neural Network (ANN), Radial Basis Function Neural Network (RBFNN), and Adaptive Neuro Fuzzy Inference System (ANFIS) in order to compare results and choose the best method for producing that estimate. The selected method was then used in the development of a novel AI model for estimating labor productivity. The developed AI model is based on Radial Basis Function Neural Network (RBFNN) after enhancing it by raw dataset preprocessing and Particle Swarm Optimization (PSO) to extract significant dataset features for better generalization. The model, named PSO-RBFNN, was selected over other techniques based on its statistical performance and was used to estimate the baseline productivity values used as the initial value in the developed system dynamics (SD) model.

In the fourth stage, a novel SD model was developed to examine the impact of change orders and different managerial decisions in response to imposed change orders on the expected productivity during the lifecycle of a project. In other words, the SD model is used to quantify the impact of change orders and related managerial decisions on excepted productivity. The SD model boundary was defined by clustering key variables into three categories: exogenous, endogenous, and excluded. The relationships among these key variables were extracted from the literature and experts in this domain. A holistic causal loop diagram was then developed to illustrate the interaction among various variables.

In the final stage, the developed computational framework and its models were verified and validated through a real case study and the results show that the developed SD model addresses various consequences derived from a change in combination with the major environmental and operational variables of the project. It allows for the identification and

quantification of the cumulative impact of change orders on labor productivity in a timely manner to facilitate the decision-making process. The developed framework can be used during the development and execution phases of a project. The findings are expected to enhance the assessment of change orders, facilitate the quantification of productivity losses in construction projects, and help to perform critical analysis of the impact of various scope change internal and external variables on project time and cost.

ACKNOWLEDGMENT

My most profound acknowledgment is to God. I want to express my sincere gratitude to my supervisor Professor Osama Moselhi and Professor Sabah Alkass for their continuous and invaluable support during my studies, for their patience, constructive guidance, encouragement, and immense knowledge. Their advice helped me during the research and writing of this thesis, and without their support and guidance, this process would have been much more challenging.

Besides my supervisors, I wish to thank Mr. Saeed Moradi sincerely, Mr. Reza Pooyan, Mr. Frazed Karimian, and Dr. Zahra Zangeneh for their not only insightful comments and constructive feedback but for the hard questions, which gave me the incentive to widen my research perspectives. My sincere thanks also go to my colleagues at Dragados Canada and Concordia University, Mr. Shakawat Chowdhury, Mr. Juan Antonio Ramiro, Mr. Amir Maher Kia, Mr. Fred Attarodi, Ms. Florentina Pana, Martin G. Barrios, Mr. Ali Emamifar, and all my friends for their support and valuable assistance throughout this research.

As my colleagues at the Construction Automation Lab, you created such a welcoming, productive, and intellectually stimulating atmosphere for me, and I am very thankful for the diversity of our team.

I owe my deepest gratitude to Ms. Farzaneh Golkhoo for her kindness, patience, and broad knowledge. She has been of great help to me for my time at Concordia University. Sincere appreciation goes to my parents Mina and Ahmad for their infinite love and care throughout writing this thesis and my life in general.

To My Mother, Mina.

You are the most excellent teacher, a teacher of kindness, love, and courage.

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List of Abbreviations

HCOi	Actual Change Order Hours During
ANFIS	Adaptive Neuro Fuzzy Inference System
ANOVA	Analysis of Variance
AI	Artificial Intelligence
ANN	Artificial Neural Network
BP	Baseline Labor Productivity
BSR	Best Subset Regression
BIM	Building Information Modeling
CLD	Causal Loop Diagrams
CMS	Change Management System
COD	Coefficient of Determination
CPI	Cost Performance Indexes
CPM	Critical Plan Method
DC	Design Changes
DFL	Direct Field Labor
DPM	Dynamic Planning and Control Methodology
EVA	Earned Value Analysis
EPC	Engineering, Procurement, and Construction
EPCM	EPC Management
EPR	Evolutionary Polynomial Regression
FRCM	Fuzzy Risk-based Change Management
FRR	Fuzzy-based Risk Ranking System
GRNN	Generalized Regression Neural Network
GA	Genetic Algorithms
PSO	Particle Swarm Optimization
JVM	Jury Verdict Method
MAE	Mean Absolute Error
MSE	Mean Square Error
MMA	Measured Mile Analysis
MTCM	Modified Total Cost Method
NBIMS	National Building Information Modeling Standard
NECA	National Electrical Contractors Association

NN	Neural Networks
Phi	Planned Hours During Period
RBFNN	Radial Base Function Neural Network
RFI	Requests for Information
RCA	Root Cause Analysis
RMSE	Root Mean Squared Error
SFD	Stocks-Flows Diagrams
SSE	Sum of Squared Errors
SD	System Dynamics
TIA	Time Impact Analysis
TPi	Impact of Change Orders in Period
TCM	Total Cost Method
TNCHR	Total Number of Change Request
TFN	Triangular Fuzzy Number

1. CHAPTER ONE: INTRODUCTION

1.1 General

According to Statistics Canada, CAD 404 billion was invested in construction, machinery, and equipment in 2014; this was a slight increase of 1.4% from 2013. Of this sum, the total contributions of public and private investments were 89 and 315 billion dollars, respectively (Statistics Canada, 2014). The construction industry can be considered as one of the largest employment sectors, contributing a substantial amount of work to the labor market and accounting for a considerable share of the gross domestic product (GDP). The GDP contribution from construction projects in Canada reached CAD 119, 902 million dollars in April 2017 (Figure 1.1). The graph below illustrates the construction GDP trend over the past ten years. The graph shows a record low of CAD 6.12 million in 1997 and the highest point of CAD 12.9 million in 2014 (Trading Economics, 2017).

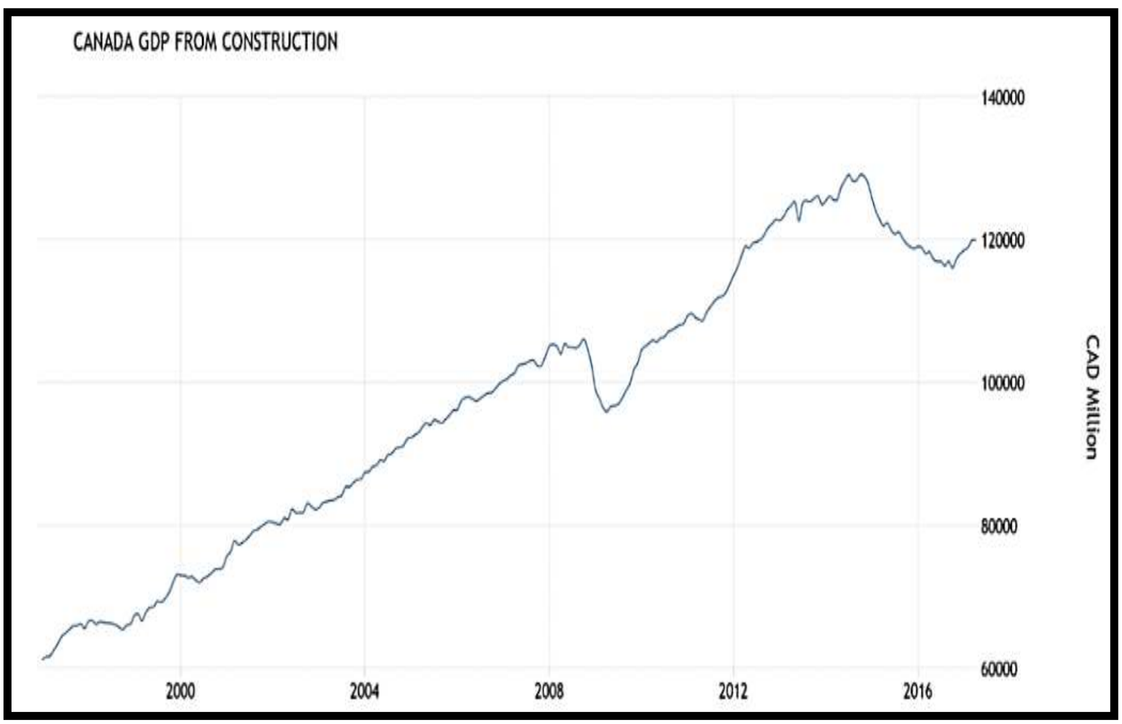


Figure 1-1. GDP Construction Trend from 1997 to 2017 (Trading Economics, 2017).

Construction projects are interesting because they are a combination of design technicality, soft and interpersonal management skills, business knowledge, and unique organizational structures, all of which represent the way people interact within projects (Ibbs and Vaughan, 2012). Construction projects are highly dependent on skilled labor supported by a management team coordinating different project stakeholders whose involvement will change over the course of a project. Construction projects are generally fast-paced environments where owners want to have the final product as soon as possible due to the value of time. This situation often leads to starting projects prior to having the final design. Moreover, the owners' expectations from the projects change constantly because of changes in the industry and economy. Thus, these factors trigger the occurrence and amplify the size and the number of change orders (Hanna et al., 1999c).

Change orders are an integral part of any construction project. Therefore, every construction contract includes clauses for managing change orders. Each change is recorded in the form of a change order, defined by Standard Construction Document CCDC 2 (2008) as follows:

"a written amendment to the contract prepared by the consultant and signed by the owner and the contractor stating their agreement upon Change in the Work, Method of adjustment or the amount of the adjustment in the contract price, if any, and Extent of the adjustment in the contract time, if any." Change orders are needed in order to arrive at a project as per the owners' and designers' needs. However, change orders are one of the main reasons for disagreements between contractors and owners. Change orders are expected to be performed by contractors in a timely fashion with fair compensation. It is obvious to all parties that change orders have a direct impact on specific tasks; however, owners neglect the ripple effect a change order will have on a project because it is not tangible during change order assessment. The direct cost of change orders is relatively easy to measure. However, contributing elements to change order costs, such as loss of productivity, the learning curve, and schedule conflicts, are more difficult to measure. Loss of productivity can be considered as one of the most common negative impacts of change orders and is very difficult to quantify.

1.2. Research Motivations

In 2015, the construction industry accounted for 7% of the GDP (Statistics Canada, 2015). The Canadian construction industry is therefore of central importance to the well-being of Canada's economy. Although overall productivity growth was relatively unchanged in the last quarter of 2014, the construction industry productivity trend showed a decline for the same period by -0.7% (Statistics Canada, 2014).

Figure 1.2 shows the labor productivity index (LPI) from 2010 to 2015 (Build Force, 2017). The LPI shows that the construction industry's productivity level is higher than that of the mining, oil and gas, manufacturing, and business sectors. Namely, the amount of money made is more per person-hour than in other industries. However, it also suggests that there should be a concern if construction productivity levels continue to decline.

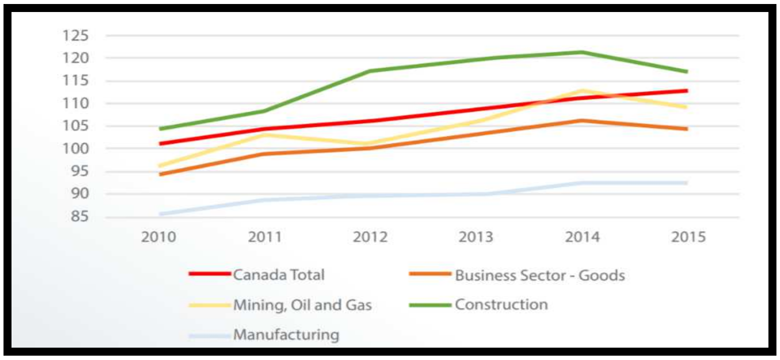


Figure 1-2. Labor Productivity Index, 2010-2015 (Build Force, 2017).

Construction projects are dynamic, multi-stakeholder and-faceted in nature, and one-of-a-kind in terms of manufacturing production. Thus, project behaviors and outcomes are not always foreseeable. Contractors prepare their estimates based on the information available in contracts and specification documents at the time of bidding. Although owners request contractors to perform independent site visits and in-depth reviews of drawings and specifications, most contractors are not be able to do so due to limited time.

As a project advances, changes are introduced to the project by different parties, mostly by owners. Project changes can be classified into two major categories: additive and deductive changes. Additive changes introduce a new scope to the initial scope of work, and deductive changes remove some segments of the initial scope. Changes that cause an increase in the original value of the contract are called extras, and those that cause a reduction are called credits (Samuels and Sanders, 2010). Regardless of their characteristics, both types of changes may disrupt to project progress (Ibbs, 2005). That is to say, changes may dramatically affect a planned project's resources in terms of quantity and availability and may require different means and methods to be carried out.

According to Schwartzkopf (2004), an increase of 5 to 10% of the total contract value should be anticipated in most construction projects due to additive changes. A 5 to 10% increase range in a 404 billion CAD dollar investment means that the direct costs of changes in 2014 were roughly 22 to 40.4 billion CAD dollars. Changes are a constant part of any construction project. Hanna and et al. (2002) define change as any action that causes alterations to the initial project scope, delivery time, or cost of work, and as inevitable in most construction projects due to each project's different characteristics and the limited resources available for planning. Lee (2007) defines change as "any act, incidence, or condition that makes differences to an original plan or what the original plan is reasonably based on." Cushman and Myers (1999) state that changes are inevitable due to the following reasons: Owner's change requirements and/or budget limitations, Errors and omissions in the design, and Differing site conditions.

However, many other factors should be taken into consideration when deciding to request changes to a project. It should be noted that not all requested changes are accepted (Lee, 2007). Each project should have a proper change management system in place in which all changes except mandatory ones are accepted or declined based on their impact on the whole project. If the contractor can estimate the impact level of each requested change, s/he can then choose to perform only the changes with acceptable impacts; the subsequent loss of productivity is then calculated considering the confirmed change requests and other influencing factors. A change order is an official contract amendment that integrates a change into the original contract (Schwartzkopf, 2004). A change order may trigger a series of changes in other parts of the project. Changes that arise as a direct result of a requested change are called "Consequential changes." Consequential changes are the outcome of a cause and effect domino relationship (Civitello, 1987). It is worth noting that in order to have a proper project change management system in place and to more precisely calculate the loss of productivity, consequential changes triggered by a requested change must be identified and considered before calculating the impact level of each requested change.

It is noteworthy to mention that 35% of change orders are caused by Design Changes (DCs); thus, effective DC management is an essential element for efficient project delivery (Lee, 2007). BIM can provide substantial assistance in dealing with DCs due to its visualization and parametric modeling capabilities. Parametric modeling uses numbers and/or characteristics to define the behavior of a graphical object and to describe relationships among model components (Autodesk, 2014). As a result, parametric modeling can improve the design process and construction management services by refining coordination, eliminating the need for extra site visits, printing, and manual drawing checks. Change in a parametric element will cause modifications in all corresponding views and locations. Warning systems can be developed among a model's components to highlight changes in any view and facilitate coordination (InfoComm, 2011).

Hanna et al. (2002) state that poorly managed changes have a notably negative effect on project performance in terms of time and cost. Change orders may impact all project participants in some way. Owners and engineers may suffer from increased overall project costs, deviation from the agreed-upon project completion date, and uncompensated time spent assessing change orders. Contractors may suffer from a shortage of cash flow, delay, unindemnified indirect costs, and loss of productivity. In the construction industry, the adverse effects of change orders on projects are widely known. However, they are difficult to quantify while being one of the major causes of disputes between owners, contractors, and sub-contractors. The effects of change orders can be classified into two categories (Ibbs and McEniry, 2008):

- Direct impact, that is the actual direct cost and time delay attributed to executing the change; and
- Indirect impact, or the effect of a change on another unchanged scope of work.

Quantifying direct cost and time required to execute a single change order is not difficult for contractors. However, precisely estimating the impact of a change on an unaffected portion of work is an arduous task. In order to implement a change, contractors may delay, interrupt, and/or execute unchanged work in a way or order different than what was initially programmed, which may lead to loss of productivity and increased cost (Ibbs and McEniry, 2008).

Moselhi (1998) classifies the cost impact of change orders into two main categories for estimating purposes: time-related and productivity-related costs. Moselhi (1998) specifies that time-related costs can be quantified once a reasonable estimate of the time and cost for executing the work has been established. Meanwhile, productivity-related costs are challenging to quantify. Owners and design professionals are skeptical about approaching the issue of loss of productivity due to change orders, and this has increased the difficulty in estimating productivity-related costs. Productivity-related costs are caused by productivity losses deducted from the level assumed to be achievable in the baseline plan. Despite the difficulties in determining productivity-related costs and skeptical attitudes from owners and their agents, these costs are factual and could be substantial if they have to be solely absorbed by contractors (Moselhi, 1998).

In order to calculate the loss of productivity, it is necessary to first define the un-impacted period or baseline labor productivity (BP) and identify the factors affecting construction labor productivity. Defining productivity in construction is not an easy task because productivity is a function of manageable and unmanageable factors (Ibbs et al., 2007). Productivity is defined as the quantitative measure of the relationship between the number of resources used and the quantity of output produced (Khan, 2005). Schwartzkopf (2004) defines productivity as the units of work completed for the units of labor used. Productivity in this research is defined as the labor work-hours required to produce the final product (Finke, 1997). Productivity is a crucial element in determining the success and failure of any construction project. Improving productivity is not a simple task due to the growing uncertainty in construction projects. Finke (1998) highlights that labor productivity is extremely variable, as it is determined by internal and external factors or conditions. Loss of productivity occurs when the actual man-hours consumed to produce the final product are higher than the planned man-hours. Conversely, when there is less accomplished work than expected, loss of productivity can be taken into account using the same amount of man-hours proposed in the initial estimation. Thus, the contractor will experience additional costs per unit of work completed. Many factors that disrupt performance efficiency can affect productivity. These factors include (Schwartzkopf, 2004): Acceleration, Out of sequence activities, Suspension, Delays, Interference, and Change orders.

A single factor will rarely result in loss of productivity; more frequently, multiple and concurrent factors, for which both parties can be held responsible, contribute to this loss (Ibbs et al., 2007). Therefore, it is essential that a proper method for measuring productivity loss due to change orders along with other influencing factors be used. This method should be able to portray realistic and precise relationships between multiple and concurrent influencing factors and policy modifications that occur during the course of a project. As mentioned previously, change order ripple effect quantification is a challenging task that requires techniques and tools adequate in showing the contributions of change orders and management policies to loss of productivity.

1.3. Problem Statement

A high degree of uncertainty is a big part of any construction project and can result in poor planning, especially when accurate information is not readily and easily available. As a project's scope progressively changes, the project team spends a considerable amount of time attempting to rectify circumstances as they occur during the course of a project (Love et al., 2010). Researchers and industry practitioners all agree that changes to construction projects are unavoidable and may become troublesome if they are not properly managed. Construction productivity fluctuates and is affected by several factors such as mode of employment, various disruptions, overall task duration, workday length, and labor composition (Khan, 2005). One of the root causes of productivity loss in construction projects is the number of changes introduced to the initial scope of work. In addition to the loss of productivity, construction project changes very often lead to prolonged disputes, delays in delivering the final product, and stoppages. Changes in a construction project pose a substantial risk for all parties; if they are poorly managed, they may become disagreements and reaching resolution for them will be a lengthy and acrimonious process. A true challenge of managing changes is the need to have a comprehensive understanding of the impacts of changes and how the effects of these changes can be reduced or prevented before they become serious problems. Despite owners and contractors acknowledging the impacts of changes, a comprehensive practical change impact quantification method is still lacking in the current body of knowledge. Construction projects are highly complex due to the interdependencies between project variables and non-linear dynamic feedback loops. Project failure may be caused when the interaction between internal and external variables that affect project dynamics is neglected (Alzraiee, 2013). Accurately quantifying the effects of changes is indispensable to project parties and can play a significant role in project success or failure. Thus, possessing a sound method to illustrate the ripple effect of change orders accurately is beneficial to all the parties involved. The method should be able to demonstrate the consequences caused by change orders in combination with the managerial policies along with some environmental and operational factors. In other words, the result will be an efficient and effective framework enhanced by a robust change management system as well as cutting edged techniques such as Artificial Intelligence (AI) and System Dynamics (SD) modeling. The model will be able to accurately assess the ripple effect of changes in construction labor productivity during the course of the project while taking into account multifaceted managerial policies as well as environmental and operational influential variables. The dynamic nature of construction projects often causes management teams to make hasty decisions without necessarily first having complete insight into that decision’s negative impacts on other project aspects. For instance, when acceleration is requested by the owner to recover delays or to shorten project duration, acceleration may impact the project in different ways. Generally, an acceleration plan leads to the hiring of a larger workforce to increase productivity and thereby shorten project duration. Conversely, a larger workforce policy may cause congestion, which will negatively impact project productivity (Figure 1.3).

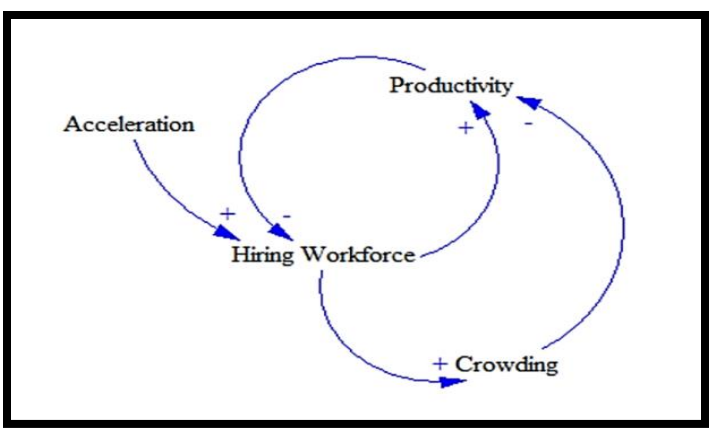


Figure 1-3. Construction Project Causal Loop Diagram.

Love et al. (2010) state that such interactions among various factors can be illustrated by employing causal loop diagrams, which can clearly show the direction and type of causality among variables. The causal loop diagram is the foundational development block of a robust SD model. SD, a continuous simulation and systems thinking approach, offers the potentials and opportunities to develop a holistic view of a complex system. This makes it a crucial tool for rectifying the complications and challenges associated with quantifying the impacts of changes on the loss of productivity in construction projects. This research aims to improve SD modeling by proposing the integration of a new AI method for improving SD modeling computation capacity and a change management system for prioritizing elective changes as well as identifying considerable changes.

1.4. Research Objectives

The main objective of this research is to address the shortcomings associated with existing methods for quantifying the loss of productivity due to change order ripple effects by developing a computerized framework that benefits from the sustainable capabilities of SD Modeling, BIM, and AI techniques. The proposed framework should be able to objectively assess the loss of productivity claims as opposed to utilizing subjective assessment, while at the same time highlighting impaired productivity root causes. Also, the developed framework can be used to facilitate what-if analysis to determine how a project will react to different managerial policy states. To achieve the main objective, several sub-objectives were considered:

1. Study various aspects of construction change orders with emphasis on their types, causes, cumulative (ripple) impacts on productivity and current methods available for change order impact quantification and their limitations;
2. Study various aspects of construction labor productivity with an emphasis on productivity loss, factors significantly affecting labor productivity, and the techniques available for measuring productivity and loss of productivity;
3. Study current productivity modeling with emphasis on the application of AI and Statistical Regression Modeling in the construction industry;
4. Study continuous simulation modeling in the construction industry and labor productivity;
5. Study contemporary BIM-based change management practices to develop a better understanding of existing methods for considering consequential changes;
6. Develop a Fuzzy Risk-based Change Management (FRCM), which includes two main modules, namely “Fuzzy-based Risk Ranking System (FRR)” and “BIM model.”

7. Adopt and modify a BIM-based model for enhancing the proposed method's visualization capabilities for capturing consequential changes;
8. Develop and compare AI and Statistical Regression Modeling to estimate baseline productivity considering environmental and operational aspects of construction projects;
9. Develop a novel NN model based on RBFNN (PSO-RBFNN) benefitting from some data processing techniques;
10. Develop a holistic qualitative causal loop diagram to demonstrate the relationship, direction, and type of causality among the key variables affecting construction labor productivity; and
11. Develop a novel quantitative SD model that can mimic the complexity of construction projects to scrutinize productivity under the different policies adopted during the course of a project.

1.5. Research Methodology

Figure 1.4 illustrates the methods used to achieve the main and sub-objectives of this research. The methodology is summarized in five phases as follows: Phase I focused on a broad literature review in the area of change orders, change order management, and the cumulative impacts of change orders with emphasis on loss of productivity. Also, a substantial literature review was performed on the state-of-the-art SD simulation modeling, BIM, Statistical Regression Modeling, and AI techniques. This phase included an overview of existing practices in change management and the quantification of the cumulative impacts of change orders. Gaps and limitations in current practices were identified in this phase, forming a solid background for achieving the research objectives, as well as the foundational block for this research. Also, this phase attempted to define the model boundary for the proposed model. The model boundary pinpoints the scope of the proposed methodology by categorizing the model's variables into three categories: environmental, operational, and managerial. Chapter 2 further elucidates these three categories. Phase II focused on the proposed methodology; the major components of the proposed model were adapted and developed based on the gaps and limitations identified in phase I and the well-established model boundary.

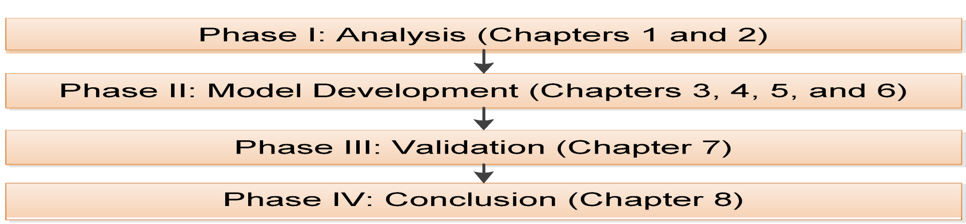


Figure 1-4. Research Methodology General Overview.

The first stage prioritized change orders so that only essential changes would be targeted using FRR. The second stage employed BIM capabilities to capture the consequential changes that may arise from the initial requested change(s). The first two steps were integrated into the FRCM. The third step was to estimate baseline productivity considering environmental and operational variables. In this step, various techniques were used including STR, BSR, EPR, GRNN, ANN, RBFNN, and ANFIS to compare their results and choose the best method for estimating baseline productivity as the BP. Based on the statistical performance indicators of the applied techniques and by benefiting from the most proper ones, a novel AI technique (PSO-RBFNN) was proposed and developed to predict BP more precisely. This step allows the BP value to be estimated and used as the initial value for the proposed SD model. The fourth stage was the development of a causal loop diagram determining the influential variables in the proposed SD model. This stage assists in recognizing those variables that need to be modeled and assessed within the next stage. In the fifth stage, a holistic quantitative SD model was developed to quantify the impact of change orders and different managerial decisions in response to imposed change orders on baseline productivity. Change orders and management policies in response to change orders cannot be assessed individually; they must be considered in relation to each other and other variables, and a system thinking approach is needed in order to develop a comprehensive view of a dynamic and complex system of change orders. To quantify the loss of productivity and simultaneously escape mathematical complexity, given operational levels with too many details and a tremendous number of equations showing the interrelationships among variables, only change orders and different managerial policies were considered in the SD modeling. Furthermore, only operational and environmental factors such as temperature, work type, gang size, etc. were considered for estimating and quantify BP using the proposed PSO-RBFNN technique and historical data. By classifying key variables into three categories: exogenous, endogens, and excluded, the SD model boundary for quantifying the impact of a change order was defined. The relationships among key variables were extracted from the literature in this domain. To illustrate various variable interactions, a holistic causal loop diagram was developed. The proposed model offers a continuous simulation and systems thinking the approach for developing a view of a dynamic and complex system. It attempts to rectify the complications and challenges associated with quantifying change impact on labor productivity loss in construction projects. Phase III included data collection from a real construction industry case study. In this phase, all the components were tested against a real case study for proposed model validation. Phase IV discussed the limitations associated with the proposed model and highlighting areas for possible improvements.

1.6. Organization of thesis

The dissertation is divided into eight chapters as follows. Chapter 2 presents a broad comprehensive literature review of change orders, including definitions, types, and causes of change orders, cumulative impacts, and influence on construction labor productivity as well as other related matters. Chapter 3 presents the methodology followed in research and a description of the development in each of its five phases. Chapter 4 explains in detail the proposed FRCM model including an FRR for prioritizing the changes and the adoption of a BIM-based model for identifying consequential changes. Chapter 5 explores two major technique categories for modeling labor productivity: Statistical Regression Modeling and AI based models. Based on the obtained performance of each technique to predict baseline labor productivity, the best techniques are selected and by benefiting from the obtained performance, a novel model (PSO-RBFNN) is developed and proposed to predicate the labor productivity more precisely. Chapter 6 covers the development of a holistic SD model designed to understand the complex behavior of construction projects at a strategic level over time through causal loops and stock-flow diagram. In Chapter 7, major components of the developed framework are validated by using a real case study information. Chapter 8 highlights the expected contributions of the research and limitations of the developed model.

2. CHAPTER TWO: LITERATURE REVIEW

2.1 Introduction

Changes in construction projects may cause serious disagreement between key project parties, client, and contractor. In construction projects, often, the magnitude of a change order is not uniform, or the scope of a change is not clear to all project parties; thus, these situations may cause delays in reaching an agreement on the resources and time required to perform a change. In addition, lack of awareness and knowledge in regards to the cumulative impact of changes in construction projects among most construction practitioners will amplify difficulties associated with managing changes in the construction industry. For example, quantifying the loss of productivity as a result of change orders in the construction industry has been a challenging task, and it requires many subjective assumptions. Lee (2007) classified construction labor productivity studies into two major categories: (a) those focused on factors affecting productivity, and (b) those focused on the quantification of productivity loss due to certain factors or change orders. Although many scholars have made significant advances in the identification of factors, these studies lack consistency in naming factors, and their scope is poorly defined (Hafze et al., 2014; Moselhi and Khan, 2010; Moselhi and Khan, 2012; Jarkas and Bitar, 2012; Dai et al., 2009). The focus of the second group is mainly on a single factor and its effects on productivity loss, neglecting the interdependencies among factors and concurrency of other factors (Hanna et al., 2008; Hanna et al., 2004; Moselhi et al., 1997; Thomas, 1992; Abele, 1986, Thomas and Yiakoumis, 1986, Golnaraghi et al., 2018). This group also suffers from data unreliability, unclear processes, and subjective assessment; therefore, their models are regarded as "black boxes" and appositeness (Lee, 2007). Meanwhile, Yitmen et al. (2006) classified researches on change order impact on labor productivity into two major groups: (a) studies focused on the execution phase or design and execution phases such as Moselhi et al. (1991a, 1998) and Leonard (1988) and (b) studies covering specific trades, such as electrical or mechanical work (Hanna et al., 1999a and Hanna et al., 1999b). This chapter is divided into two major sections. The first section covers the concepts and the background to change and productivity in the construction industry. The descriptions of major terms and concepts in the industry such as productivity, efficiency, performance, and change are explained more in-depth here. The second section focuses on the concepts related to the tools and techniques for measuring the loss of productivity and sets the background. The first part of the chapter offers background on change and productivity in three main sections. Section 2.1 is a general overview of change and productivity concepts in the construction industry. Section 2.2 covers the concept of change in construction more in-depth and covers type of changes, causes of changes, change impacts, cost components of changes, pricing methods, the timing of changes, disruption and changes, to end with change management. Section 2.3 focuses on productivity in the construction industry. It starts with the definition of construction labor productivity and is followed by how productivity is measured, factors affecting productivity, loss of productivity, and techniques for measuring the loss of productivity. The second part of the chapter includes four major sections related to the tools and techniques used in this research. Section 2.4 covers the definition and background of SD and its application in project management. Section 2.5 introduces the concept of ANNs and different type of ANNs. Section 2.6 covers BIM and its application in change management systems. This chapter ends with findings, limitations, and gaps in the body of knowledge.

2.2 Change in Construction

As a project progresses, its scope may change due to many obvious and clear causes. Change unquestionably takes place during the course of a project regardless of size or complexity. The Construction Industry Institute (CII, 2000) defines change as "any event which results in a modification of the original scope, execution time, or cost of work being inevitable on most construction projects due to the uniqueness of each project and the limited resources of time and money available for planning." A survey conducted to identify major causes of delay for mega projects in Saudi Arabia by Assaf and Al-Hejji (2006) showed that only one cause of delay is common among all project parties (client, contractor, and consultant), changes imposed by the client during the construction phase. Figure 2.1 illustrates the different phases of a construction project and how changes can be incorporated into a contract. Changes are integrated into a contract using addenda prior to the bid-opening phase. During the bid-opening, and until the agreement has been signed, known as the bid-opening period, no changes are allowed. After the contract has been signed, any change orders need to be integrated into the contract through a change order process as outlined in the contract (Fisk and Reynolds, 2013). A change order is a written agreement signed by project parties. It authorizes the contractor to affect a modification in the terms of the contract. It should be noted that a change order does not always increase contract value; it is possible for a change to be in the form of credit or for there to be no cost increase at all. Despite the fact that change orders should always be written agreements, enforced by change management clauses in any construction contract, oral change orders are very common in construction projects. Client and contractor action or inaction can waive the written change order obligation, a risky approach to managing changes.

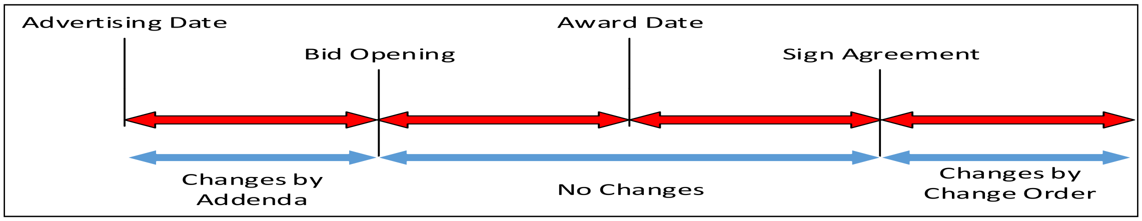


Figure 2-1. Timeline of Changes by Addenda vs. Change Order (Fisk & Reynolds, 2013).

Moselhi et al., 2005 found that clients and contractors face serious challenges due to change orders. However, change orders are an essential means to satisfy clients' requirements as well to effectively solve issues caused by errors and omissions, construction techniques, and inaccurate contract documents. A change order can be classified into one of three groups (Hanna et al., 1999a): 1) An addition, deletion, or revision in the original scope of work; 2) A modification in the contract value, if any; and 3) A modification in the contract duration, if any. It is worth mentioning that change orders are legally enforceable in court. The different types of change orders will be explained in more detail in the following sections.

2.2.1 Types of Changes

Change orders are classified under one of seven distinct major categories that fall into the following categories:

1. Bilateral Changes: The client may order a change at any time during the course of a project. Prior to introducing a change, the client requests the contractor to provide an estimate of the cost and time impact of said change. Based on the contractor's response, the client will decide to initiate that change or not (Callahan, 2005). According to Civitello (1987), client-acknowledged change orders (bilateral change orders) are the only type of changes to be incorporated in the client's budget and this type is the least disputed. However, many clients and consultants fail to recognize or entirely reject the consequential impacts of change orders; instead, they simply accuse the contractors of poor planning and poor performance. Consequential impact costs are usually left to be absorbed by contractors or to be recovered through litigation, if possible.

2. Constructive Changes: A constructive change order occurs when the clients' or their representatives' actions or inactions force the contractors to perform extra work. Gusman (1973) classifies constructive changes into three broad groups as follows: 1) Deficiency in drawings or specifications. This group forces contractors to perform extra work; 2) Contract misinterpretation, such as requiring a higher standard. This may cause contractors to perform extra work, and 3) Neglecting a valid time extension by client thereby forcing the contractor to meet the original baseline schedule. These cause extra costs to contractors. It is very common for clients to reject or not acknowledge constructive changes. Therefore, there are usually no change orders for these types of changes. It is highly recommended that the contractor take the necessary steps to document all the events and facts that create the need for constructive changes; in doing so, the contractor may be able to secure compensation for constructive changes (Civitello, 1987).

3. Unilateral Changes: Unilateral changes are those changes where the client requires a contractor to perform directed changes. Unilateral change clauses can be found in most change clauses. The contractor is bound by the contract to perform these changes, regardless of whether or not the clients have agreed to the reimbursement or if the contractor is willing to do it. Despite the fact that disagreement exists in any project, the clause covering unilateral changes is essential to the client because it allows the client to stay in charge of a project as it nears completion. Clients usually include contract provisions that specify the contractor shall immediately comply with such directives (Richter and Mitchell, 1982).

4. Cardinal Changes: A cardinal change is one where a client introduces excessive changes to a project, beyond the initial scope agreed upon at contracting phase. It should be noted that change procedures and costing do not include a formula to compensate for the cost of this type of change. Increased cost due to cardinal changes may be possible to compensate for in terms of quantum merit (Silberman, 2002). The concept of cardinal changes is often applied in cases of design defects that result in extreme changes to a project. Change magnitude and quality are major factors to consider when evaluating if a change is cardinal (Kuprenas, 1988). A cardinal change is considered a breach of contract by the client and may occur at several circumstances. One situation is when a client directs their contractor to perform a change outside of the scope agreed upon in the contract. Another is when a client introduces various or radical changes that cause the project to divert substantially from what was agreed upon during the contracting phase (Hanna and Swanson, 2007). Callahan (2005) states that the definition of a cardinal change may fall under one or a combination of circumstances: 1) A prolonged project duration compared to the initial time agreed to in project contract; 2) Higher costs for securing raw material; 3) Different materials are required based on the client's post-contract requirements; 4) Changes in equipment or tool requirements; 5) Greater labor demands or more skilled laborer requirements than those projected; 6) A considerable increase in the size of the project; and 7) A significant increase in the quantity of items to be produced. Because a cardinal change is considered a breach of contract caused by the client, contractors may be released from their obligations as stated in the contract and allowed to be compensated for labor, material, and equipment costs incurred by the project, including reasonable markup and profit (Callahan, 2005).

5. Consequential Changes: Consequential changes occur as a direct result of other changes. In other words, they are the outcome of a domino relationship between cause and effect. The cost components of consequential changes are direct costs of changes, costs associated with rework, resequencing, etc., and impact costs (Civitello, 1987).

6. Deductive Changes: This type of change is under the sole control of the client. Change clauses usually allow the client to remove a portion of the project scope, an action known as a deductive change. There are several problems associated with deductive changes. First, the change should be limited to those changes that fall under the scope of the work as agreed to in the contract. Therefore, a deductive change cannot be assessed by the same principle. Secondly, a deductive change may be considered a violation of the obligation of good faith because a deductive change will affect a contractor's profit. Finally, a deductive change may be considered a breach of contract if a solid explanation is not forthcoming. If a client wishes to delete a portion of the pre-agreed upon work, it is recommended that the client provide sound and concrete reasons or at least act in good faith (Sweet and Schneier, 2012).

7. Discretionary and Mandatory Changes: Diekmann and Nelson (1985) classified changes into two broad groups: discretionary and mandatory changes. Discretionary changes are those caused by an omission in the initial scope's definition or a variation in the owner's requirements and new regulations or statues cause mandatory changes.

2.2.2 Causes of Changes

The causes of changes are actions and situations that contribute to or initiate a change in construction projects. Sun and Meng (2009) classified causes of changes into five categories: project-related, client-related, design-related, contractor-related, and external factors (Table 2.1). Sun and Meng explain each category as follows: project-related causes and client-related causes.In project-related causes, the uniqueness and often the complex character of construction projects increases the probability of changes occurring during the course of a project.

Client-related causes are triggered by deviation from the client's initial requirements and standards and are very common, particularly in the design stage. Unrealistic contract durations imposed by clients, client-initiated variations, and requirement changes are the most common client-related causes of change. In design-related causes, a major contributor is a human error. Design errors and omissions are caused by architects and engineers (A/E).

Table 2-1. Causes of Changes Taxonomy (Sun and Meng, 2009).

	Chan and Kumaraswamy, 1997	Hsieh et al., 2004	Wu et al., 2004
Project-related	• Project construction complexity • Very slow decision-making involving all project teams • Lack of communication between client, consultant, and contractor • Slow and/or incomplete information flow between project team members	• Site safety considerations • Site security considerations • Safety facilities reinforcement • Project complexity	• Site restrictions • Delays in securing the site, equipment, or materials
Client-related	• Client-initiated variations • Unrealistic contract durations imposed by the client		• Required changes
Design-related	• Required work variations • Design information delay • Long waiting time for the approval of drawings • Mistakes and discrepancies in design documents	• Defects in design and planning • Errors and omissions in quantity estimations • Inconsistency between drawings and site conditions • Inadequate specifications	• Design changes in response to site conditions • Erroneous or incomplete design information • Insufficient site investigation prior to design
Contractor-related	• Poor site management and supervision • Inadequate managerial skills • Improper control over site resource allocation • Inadequate contractor experience • Contractor deficiencies in planning/ scheduling the preconstruction stage	• Inadequate planning • Lack of contractor experience	• Changes in construction methods • Poor workmanship • Poor scheduling
External factors	• Unforeseen ground conditions	• Unforeseen site conditions • Regulation changes • Change in the decision-making authority • Unpredictable • weather conditions	• Legislative or policy changes • Political pressure • Natural disasters • Unexpected geological conditions

Long waiting times for approval of drawings, citation of inadequate specifications, and design changes in response to site conditions are very common in this category. In contractor-related causes involving medium- and large-sized projects, general contractors are responsible for planning and managing the whole process. Poor planning and lack of management skills are the main causes of project change and poor performance. Poor workmanship and lack of coordination among sub-contractors are widely recognized as the most common reasons for unplanned changes (Sun and Meng, 2009). Construction projects are subject to the influence of environmental factors such as rain, wind, humidity, and temperature, as these are referred to as external factors. These factors may cause slowdowns and work stoppages (El-Rayes and Moselhi, 2001). Hsieh et al. (2004) reviewed 90 metropolitan public work projects in Taipei to identify and categorize the causes of changes. Hsieh et al. (2004) used statistical correlation and variance analysis to identify the connections among various change causes. The results of their study can be used as guidelines in change management procedures. Hsieh et al. (2004) classified the causes of changes into two major categories: "technical" and "administrative." Under the technical category, there are four sub-categories: planning and design, underground conditions, safety considerations, and natural incidents. The administrative category contains five sub-categories: changes in work rules and regulations, changes in decision-making authority, special requirements of project commissioning and ownership transfer, neighborhood pressure, and miscellaneous. Keane et al. (2010) conducted a literature survey from which they grouped change causes based on contracting parties as client-related, contractor-related, consultant-related, and non-party related causes (Table 2.2) defined as:

- Client-related causes can arise due to a change in project scope, client financial problems, insufficient project objectives, the replacement of materials or procedures, obstacles to a prompt decision-making process, client behavior, and a client change to the specifications (Keane et al., 2010);
- Consultant-related causes are those due to design or specification changes requested by the consultant, errors or omissions in design, conflicts among contract documents, technology changes, value engineering, a lack of coordination, design complexity, inadequate details in the working drawings, poor knowledge of available materials and equipment, a consultant's lack of required data, and ambiguous design details (Keane et al., 2010);
- Contractor-related causes can occur due to a lack of participation in the design phase, the absence of required equipment, lack of skills, contractor financial problems, inaccurately-anticipated profitability, unanticipated site conditions, poor work quality, unfamiliarity with local conditions, fast-track construction, poor procurement and material handling processes, poor communication, long-lead procurement, overly complex design and technology, and a lack of strategic planning (Keane et al., 2010); and
- Non-party related causes are those causes not under the control of contracting parties. These include factors such as weather conditions, health and safety, changes in

economic conditions, sociocultural factors, and any other unforeseen problems (Keane et al., 2010).

Table 2-2. Change Causes (Kean et al., 2010).

Client-related Causes	Consultant-related Causes	Contractor-related Causes	(Non) party-related Causes
Change of plans or scope (CII, 1990b)	Change in design (Arain et al., 2004; Fisk and Reynolds, 2013)	Lack of involvement in design (Arain et al., 2004)	Weather conditions (Fisk and Reynolds, 2013; O'Brien, 1998)
Insufficient planning at the project definition stage or lack of involvement of the owner in the design phase (Arain et al., 2004)	Errors and omissions (Arain et al., 2004)	Unavailability of equipment (O'Brien, 1998)	Safety considerations (Clough et al. 2015)
Owners' financial problems (Clough et al. 2015; O'Brien, 1998)	Conflicts among contract documents (Ibbs et al., 1986)	Skills shortage (Arain et al., 2004)	Change in economic conditions (Fisk and Reynolds, 2013)
Inadequate project objectives (Ibbs and Allen, 1995)	Technology change (CII, 1994b)	Financial problems (Thomas and Napolitan, 1995)	Sociocultural factors (O'Brien, 1998)
Replacement of materials/ procedures (Chappell and Willis, 2013)	Value engineering (Dell'Isola,1966)	Desired profitability (O'Brien, 1998)	Unforeseen problems (Clough et al. 2015; O'Brien, 1998)
Lack of a prompt decision-making process (Sanvido et al., 1992; Gray and Hughes, 2001)	Poor coordination (Arain et al., 2004)	Differing site conditions; poor workmanship (Fisk and Reynolds, 2013; O'Brien, 1998)	
Obstinate nature of the owner (Wang, 2000; Arain et al., 2004)	Design complexity (Arain et al., 2004; Fisk and Reynolds, 2013)	Fast-track construction (Fisk and Reynolds, 2013)	
Change in specifications by owner (O'Brien,1998)	Poor working drawing details (Geok, 2002; Arain et al., 2004)	Poor procurement process (Fisk and Reynolds, 2013)	
	Poor knowledge of available materials (Geok, 2002)	Lack of communication (Arain et al., 2004)	
	Lack of required data (Arain, 2002)	Lack of experience	
	Ambiguous design details (O'Brien, 1998)	Long-lead procurement (Fisk and Reynolds, 2013)	
	Poor design (CII, 1990a; Fisk and Reynolds, 2013)	Complex design and technology (Arain, 2002)	
	Change in specifications (O'Brien,1998)	Lack of strategic planning (Clough et al. 2015)	

Based on the analysis of the abovementioned causes, Kean et al. (2010) suggested that the quality of consultancy services and securing financial resources are topmost factors for the client in the contracting phase. The client's approach towards the other parties also has a real effect on change causes. Non-party related causes should not be neglected when considering risk in the contracting phase. Regardless of the causes of changes, almost all changes have something in common: project performance disruption. Time and cost impacts are the frequent direct result of poorly managed changes.

2.2.3 Change Order Impacts

Change orders are an essential tool for clients when managing their project, uniting their goal of successful project completion and rectifying unfavorable situations that may arise due to errors and/or omissions in the design, construction methods, or contract documents. However, change orders pose a negative impact on major construction project aspects such as productivity, as well as causing cost overruns and costly disputes (Moselhi et al., 2005). An imposed change may severely affect a project and jeopardize its success. The impact of any change may be direct or indirect and may lead to loss of productivity. The impacts of change orders on a project are known to industry professionals, but their quantification is not a straightforward process. The impacts of change orders are not only the direct costs of the additional resources required performing the change but also how the change interrupts the flow of unchanged work. This phenomenon is called the cumulative impact of change orders. The chief element of a cumulative impact is the effect of change orders on unchanged work. It is worth mentioning that the impacts of change orders are considered the cost effect on the changed and unchanged scope of work. A common practice in the construction industry is that clients request information about the cost impacts associated with any proposed changes in advance in order to decide whether to allow these changes or not. Contractors generally try to claim impact costs based on a lump sum calculation submitted upon completion of the project. This lump sum is calculated based on a more universal assumption of cost because impact costs cannot be isolated for a specific change or be estimated ahead of time due to the interdependencies of construction activities (Moselhi et al., 1991). The interaction among changed and unchanged components of work produces a synergistic impact cost that is greater than the impact cost of each individual change when assessed independently. Table 2.3, developed by Sun and Meng (2009), summarizes the change effects proposed by Manzoor Arain and Pheng (2005), Hanna (1995 and 2005), and Bower (2000). Before explaining how the impact of change orders is quantified, it is important to first understand cost components and change order pricing techniques.

2.2.4 Timing of Changes

Although change is a tool for managing project time and cost more effectively throughout its course, mismanaged changes may increase the cost of projects and cause lengthy delays.

Change may affect many aspects of a project and become a serious and expensive problem for project parties. According to Ibbs (2005), one change characteristic that has not been adequately scrutinized is the issue of a change's timing. Ibbs et al. (2001) state that the timing of a change is a key factor in determining, if a change will be favorable or unfavorable to a project. A suggestion at an early phase of a project's life cycle may be beneficial, but the same suggestion later in the project may have a severe negative impact on cost and schedule. Changes issued when less than 10% of a project's physical progress has been completed tend to have a less negative impact than changes in later phases.

Table 2-3. Summary of Change Effects (Sun and Meng, 2009).

	Arain and Pheng	**Hanna**	**Bower**
Time-related	Delay in payment Material and equipment procurement delay Logistics delay	Time extension Overtime Rework	Time lost in stopping and restarting Rework Standing time for subcontractors
	Rework and demolition Completion delay	Re-planning	
Cost-related	Increased costs Increased overheads Additional payments to the contractor	Increased costs Adjustment in crew makeup Overtime costs Compensation	Loss of earnings Increased time- and material-related charges Increased overheads Change in cash flow
Productivity-related	Productivity degradation	Schedule compression Out-of-sequence work Trade stacking Over manning Loss of learning curve Multiple-shift work	Reprogramming Loss of rhythm Unbalanced gangs
Risk-related	Affected progress	Acceleration Interruption Interference Site congestion	Acceleration Loss of float Increased sensitivity to delay
Other effects	Poor professional relations Claims and disputes Poor safety conditions Quality degradation Damage to reputation	Co-ordination problems Less-qualified labor Loss of morale	Revision to project reports and documents Winter working

Ibbs (2005) studied 162 disputed and non-disputed projects from 93 different entities and measured change in absolute terms, meaning that a project's deductive and additive changes were treated the same regardless of their signs. The reason for using an absolute term was that deductive changes, just like additive change, have the potential to affect project productivity, as (Equation 2.1) demonstrates:

$$|Value\ of\ Change| = \begin{cases} -Value\ of\ Change, & Value\ of\ Change < 0 \\ Value\ of\ Change, & Value\ of\ Chnage > 0 \end{cases} \qquad Equition\ 2.1$$

Ibbs (2005) concluded that late changes were more detrimental to productivity than early changes. In fact, he found that late changes often resulted in a productivity ratio of less than 1.00, a substandard rate. Later changes have a more a detrimental impact on a construction project since later phases are difficult to re-plan and re-schedule, resulting in the substantial additional rework because the project characteristics and settings have changed. Thus, with late changes, the advantage of the learning curve is lost and inefficiency will occur (Hanna et al., 1999a). Hanna et al. (1999b) proposed that the effect of a change timing on project productivity has a linear characteristic from inception to completion. This assumption has a major drawback; it neglects the ripple effect of change orders on the remaining unchanged work (Moselhi et al., 2005). To overcome this drawback, Moselhi et al. (2005) performed an in-depth study of 33 construction projects in the United States (US) and Canada. The first step was to plot the direct filed labor (DFL) hours that represent the utilization of DFL hours over the construction phases (Figure 2.2). In all 33 cases, the construction project durations were divided into five equal periods and the DFL man-hours ratio calculated for each period to show the value of the scope of the work expressed in man-hours. Moselhi et al. (2005) introduced a new parameter, the timing impact of change orders (TPi). The TPi is calculated as follows (Equation 2.2):

$$TPi = \frac{HCOi}{PHi} \qquad Equation\ 2.2$$

Where TP*i* is the timing impact of change orders in period *i,* HCO*i* is the actual change order hours during the period *i,* Ph*i* is the planned hours during the period *i;* and *i* is the period when the change order occurs (*i*= 1 to 5).

Moselhi et al. (2005) proposed that a new parameter can consider the combined impact of two factors: (a) the timing of a change order and (b) the magnitude of the change orders in each period. A prototype NN was developed to measure productivity loss by incorporating TP_i, the type of work (TW), and the type of impact (TI), which is either a single change order or change orders and one or two additional causes of productivity-related issues. In summary, "When evaluating change orders, regardless of their cause, the most significant factor is when the change occurs" (Coffman, 1997). Although changes in the early stages of a project are less detrimental to project success, those changes have substantial and often unanticipated impacts on later project states. Thus, changes should be managed in a timely fashion to avoid their costly impact later in a project (Ibbs, 1997; Ibbs, 2012).

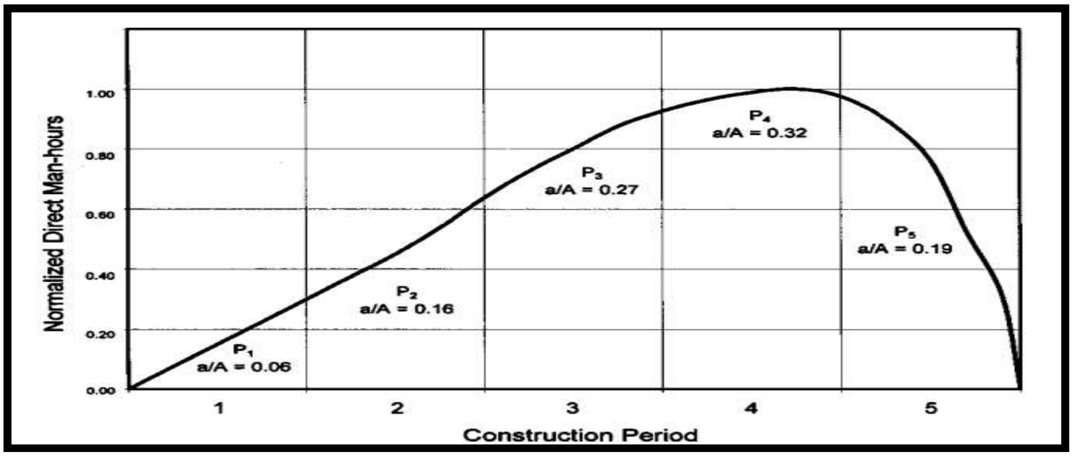


Figure 2-2. Direct Manpower Loading for Analyzed Cases (Moselhi et al., 2005).

2.2.5 Disruption and Changes

The construction industry still faces a serious challenge in being able to identify the scope or magnitude of change-caused disruptions at the activity and project level. This challenge weakens contractors' position in negotiating change orders, making it difficult for contractors to take all the necessary measures to mitigate the disruptive effects of change orders (Finke, 1998), increasing the probability of change orders turning into claims and disputes.

Disruption can be defined as loss of productivity, disturbances, the need for rework, idle or downtime caused by a lack of tools or equipment or any other reason, and interruption to the original work or planned construction methods causing inefficiencies (Thomas and Napolitan, 1995). Disruption may be easily overlooked because there is no variation in the planned quantities or in the initial scope of the interrupted work, and the interrupted work is still utilizing the planned resources, means, and techniques. It should be taken into account that unchanged work includes the initial work scope and changes introduced previously and/or simultaneously to the specific change being scrutinized (Finke, 1998). To better understand the concept of disruption, a disruption scenario adapted from Lee (2007) was built into Figure 2.3 to demonstrate how a delay in response by the client can cause different types of disruptions, such as congestion, errors, stop and go operations, and rework that may cause a loss of productivity. A full description of the example can be found in Lee's (2007) doctoral dissertation, University of California, Berkeley. As previously discussed, changes should be managed in a timely fashion to mitigate associated disruptions. If managers take appropriate action, a project can get back on track. However, the feedback from corrective managerial actions may cause more disturbances in a project. Delays will often occur if disruptions are not managed as they should be.

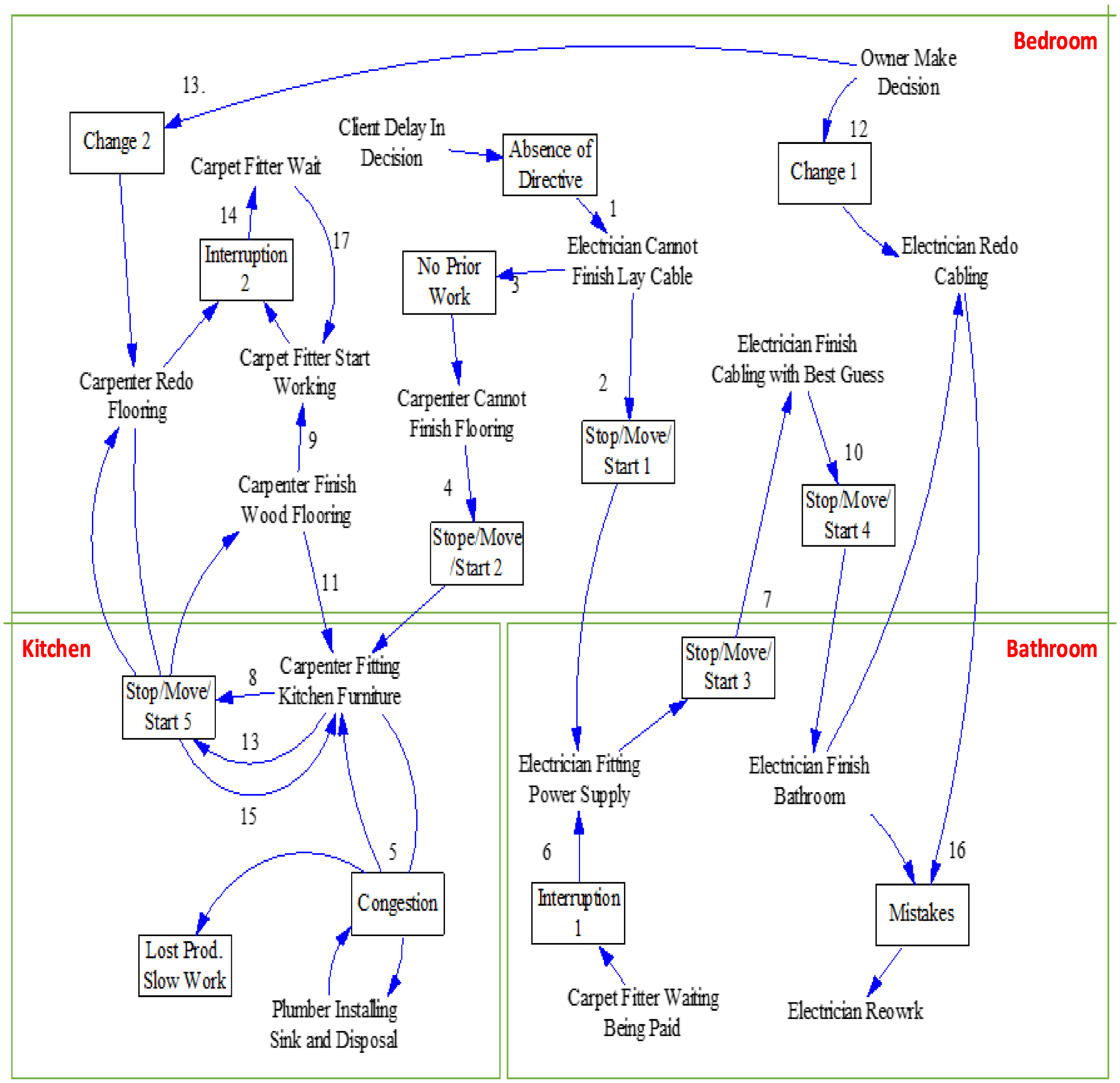


Figure 2-3. Illustration of a Disruption Case (Lee, 2007).

One of the corrective actions for rectifying delays in construction projects is acceleration. Acceleration can be performed via different techniques in a construction project, such as overtime, different work sequences, and work shifts. Thus, a project may face larger labor needs, with larger work crews, and the overlap of work among trades. Each of those situations can cause disruption in the form of productivity losses if they are poorly managed. If acceleration is not properly managed, a project may experience even more disruptions and delays. In this case, project parties will become more reliant on acceleration to rectify the situation, leading to a vicious cycle as illustrated in Figure 2.4 (Lee, 2007).

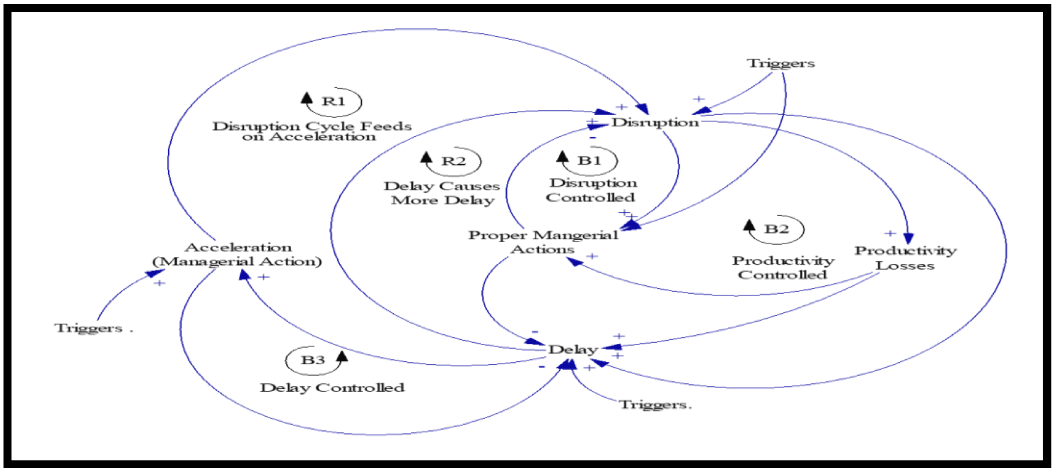


Figure 2-4. The Vicious Cycle of Disruption (Lee, 2007).

To minimize the impact of acceleration, sufficient engineering support should be available for better planning and timely procurement during the acceleration period. It is worth noting that the support services should be in acceleration mode (Schwartzkopf, 2004).

2.2.6 Change Management

Change management is an essential part of construction project management, as changes may cause delays and disruptions and quantifying change impacts is difficult and troublesome. Therefore, even a small advancement in change management procedures may easily go a long way towards saving a project (Motawa et al., 2007; Gunduz, 2002). Change management is an art and science, illustrating the relation among the influential internal and external change factors that may be detrimental or beneficial to a project. Project Management Body of Knowledge (PMBOK) introduced integrated change control (Figure 2.5) as "the process of reviewing all change requests, approving changes and managing changes to the deliverable, organizational process assets, project documents and project management plan" (PMI, 2013).

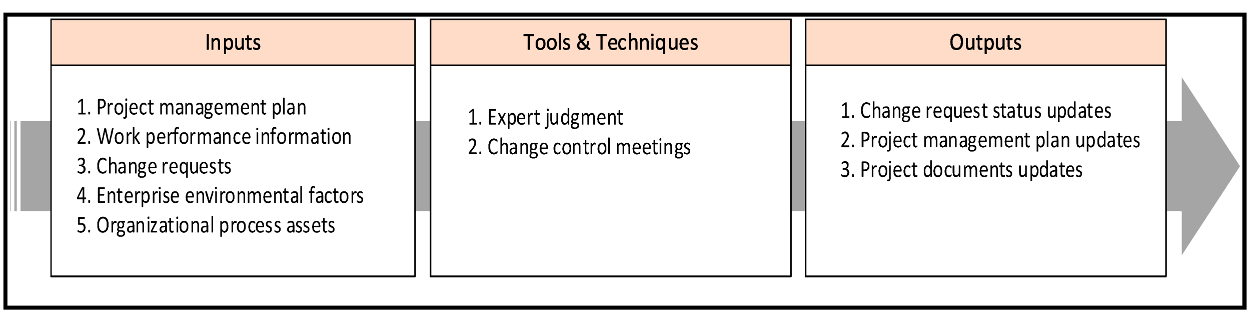


Figure 2-5. Integrated Change Control – Inputs, Tools & Techniques, and Outputs (PMBOK, 2013).

Change management includes identifying potential changes, pinpointing the changes that have occurred, planning to mitigate the impacts of changes, and managing changes during the course of a project. Change management is closely tied to all project processes and functions that are subject to change: scope, time, cost, quality, risk, contract, resources, tools and techniques, schedule, and other key integrative processes (Voropajev, 1998).

Ibbs et al. (2001) proposed a holistic project change management system (CMS) that has two levels, one for principles and another for the management process. Ibbs et al.'s CMS focuses on the first level and is structured on the following principles, applied in successive steps:

I. Support a balanced change culture: Communication and documentation are the basic principles of change management. At this stage, project success factors should be communicated and documented among all project parties. Two concepts are introduced to the project team: beneficial changes and detrimental changes. It should be noted that the timing of a change is very important, as it can transform a beneficial change into a detrimental one (and vice versa) (Ibbs et al., 2001);

II. Identify changes: The second step in effective change management is to identify changes in a timely fashion. Early identification makes it easier to manage changes and the earlier a change occurs in the course of a project, the easier it is to mitigate and manage its effects. As with the previous principle, good communications and proper documentation are very important. The project team members decide whether changes are "required" or "elective" (Ibbs et al., 2001);

III. Assess each change: CMS must assess each change, i.e., a management team should decide to either accept or execute a change or reject it. The management team needs to rapidly assess high priority (required) changes to avoid costly delays. At this stage, the elective changes should be further analyzed to determine if they offer a considerable benefit to the project (Ibbs et al., 2001);

IV. Implement changes: Implementing and tracking changes are the key reasons to have a change management system in place. This step requires the continuous monitoring of each change's implementation. This monitoring allows the project team members to rectify any other problems that occur after executing a particular change (Ibbs et al., 2001); and

V. Assure continuous improvement: Last but not least, this principle ensures learning from the errors and events caused by changes. The main purpose of this stage is to determine the root causes in order to enact corrective measures to rectify errors and reduce the need for similar changes in the future (Ibbs et al., 2001).

In order to integrate errors into a change management system, Lee and Pena-Mora (2005) developed an SD model to illustrate the error feedback processes. Their proposed method shows that SD can provide a holistic view of complex systems and highlight which strategies should be adopted to improve project performance.

Motawa et al. (2007) developed an integrated change management system to show the major decisions required to execute changes and to mimic the iterative cycles of concurrent design and construction that arise from unforeseeable changes and their associated impacts. The system was developed by incorporating a fuzzy logic-based change forecasting model associated with SD, called Dynamic Planning and control Methodology (DPM). Their proposed system can be utilized for: (a) robust planning and control actions, (b) improved understanding of the dynamic nature of change impact feedback loops, (c) considering a reasonable allowance for prospective changes in a project's planning phase, (d) identifying the cause and effect interactions of change events, and (e) studying the impact of change on project key parameters. Similar to many SD models in the literature, this system requires a more detailed study to establish sound mathematical relationships among project variables.

Zou and Lee (2008) scrutinized the relationship between change management practices and cost performance. Using data extracted from the CII Benchmarking and Metrics database, they performed statistical analysis (one-way ANOVA) to highlight the efficiency of individual change management approach components in controlling project cost. They used linear regression analysis to investigate the overall usefulness of change management practices in controlling project change cost. Their results show that individual change management practice elements have different levels of leverage in helping to control project change cost. In addition, they found that using change management practices is truly helpful in lowering the proportion of change cost in project actual cost. Projects with a prepared contingency plan for critical changes, a systematic change justification procedure, and clear clauses in their contract on how to handle changes appear to have a very low chance of experiencing a significant change in planned cost compared to the actual project cost. Furthermore, projects typically do better in terms of project change cost performance when their changes are assessed against a project's business drivers and success criteria. Sun et al. (2006) developed a change management tool kit that can provide a standard framework for supporting change management in construction projects. Their proposed model deals with important aspects of change management, forecasting change, and responding to change by rearranging workflows. However, their model has some shortcomings, listed below (Sun et al., 2006): 1) Additional validation trials are required prior to its adoption in real cases; 2) The proposed tool is not fully automatic and it requires manual user input and thus increases the likelihood of human error, and 3) The proposed tool suffers from a lack of integration between workflow and a prediction tool.

2.3 Construction Productivity

The Association for the Advancement of Cost Engineering (AACE, 2004a) defines productivity as “a relative measure of labor efficiency, either good or bad when compared to an established base or norm.” Construction labor productivity is one of the most researched topics because of the construction industry’s substantial contribution to overall economic health. Construction labor productivity is also considered a good indicator for evaluating project success or failure. In other words, construction labor productivity has significant effects on not only the economic conditions of the construction industry but is also a major player in the larger economy. Construction labor productivity is a true reflection of the financial success of a project. The efforts to measure productivity loss in construction projects has led to an array of productivity terminology, significant discussions regarding productivity and project performance, and the discovery of a considerable amount of external and internal productivity factors that affect a construction project’s lifecycle.

Unlike other industries, the US Bureau of Labor Statistics (BLS) is not able to publish productivity indices for the construction industry due to a lack of “suitable data” (Allmon et al., 2000). The following sections offer some background information regarding productivity, productivity measurement techniques, factors affecting productivity, performance, loss of productivity, and measuring the loss of productivity with respect to the abovementioned concerns.

2.3.1 Definition of Construction Labor Productivity

Productivity is a delicate aspect of any construction projects. The Oxford Dictionary defines productivity as “the state or quality of being productive” or “the effectiveness of productive effort, especially in industry, as measured in terms of the rate of output per unit of input” (Oxford Dictionary, 2015). Three key elements of the concept of productivity are indicated in the following definitions (Yi and Chan, 2014): The state or quality of being productive is the strength behind construction; Effectiveness is the degree to which productive effort is utilized efficiently in constructing a preferred result; and Rate is a measure of output against input over a finite time interval. Unquestionably, the definition of productivity in construction can cause some confusion because of the various different ways to define it. Strictly speaking, productivity is a component of cost and not a tool for measuring cost. It is not a method for estimating the cost of resources but is instead a quantitative assessment of the correlation among the amount of resources used and the amount of output made (Khan, 2005). Consequently, productivity in construction is considered as a measure of output that is achieved by a combination of inputs. By considering this perspective, two concepts of measuring productivity have been summarized (Yi and Chan, 2014):

I. Total Factor Productivity (Equation 2.3): This is the most common measurement technique of construction productivity. The output is measured against all inputs, as shown in Figure 2.6 (Goodrum and Haas, 2002). Total Factor productivity is a very advantageous economic model for developing the strategy and assessing the state of the economy; however, it is not beneficial to contractors (Park, 2006; Thomas et. al., 1990). It is calculated as:

$$Total\ Factor\ Productivity = \frac{Physical\ Ouput(units)}{Labor(S) + Circulating\ Capital(S) + Fixed\ Captial\ (\$)} \qquad Equation\ 2.3$$

Where

a. Circulating Capital: Any kind of capital that will be depleted during the course of a project, such as material and operating expenses, and
b. Fixed Capital: This refers to any kind of capital that is not exhausted during the course of a project.

II. Partial Factor Productivity (Equation 2.4): This is referred to as single factor productivity, in which output is measured against a single input or selected inputs and calculated as:

$$Partial\ Factor\ Productivity = \frac{Physical\ Ouput(units)}{Labor(S) + Fixed\ Captial\ (\$)} \qquad Equation\ 2.4$$

In most construction projects, the labor cost is 30 to 50% of total project cost (Gupta and Kansal, 2014). Construction is regarded as a labor-intensive industry and it can be assumed that labor is the governing productive resource, hence, productivity is chiefly contingent on labor productivity (Yi and Chan, 2014). Another misperception that can arise from construction labor productivity is when the ratio is based on man-hours and work accomplished. Although hourly outputs are very commonly used to measure labor productivity in which a single output is measured against a single input (Hanna et al., 2008; Thomas and Yiakoumis, 1987), they should not be considered as indicative of labor performance (Khan, 2005). The following productivity equations (Equation 2.5) and (Equation 2.6) are the most widely used in the literature (Thomas et al., 1990):

$$Productivity = \frac{Output\ (\$)}{Input\ (Labor\ \$)} \qquad Equation\ 2.5$$

$$Productivity = \frac{Input(labor\ \$)}{Output(Man - hours)} \qquad Equation\ 2.6$$

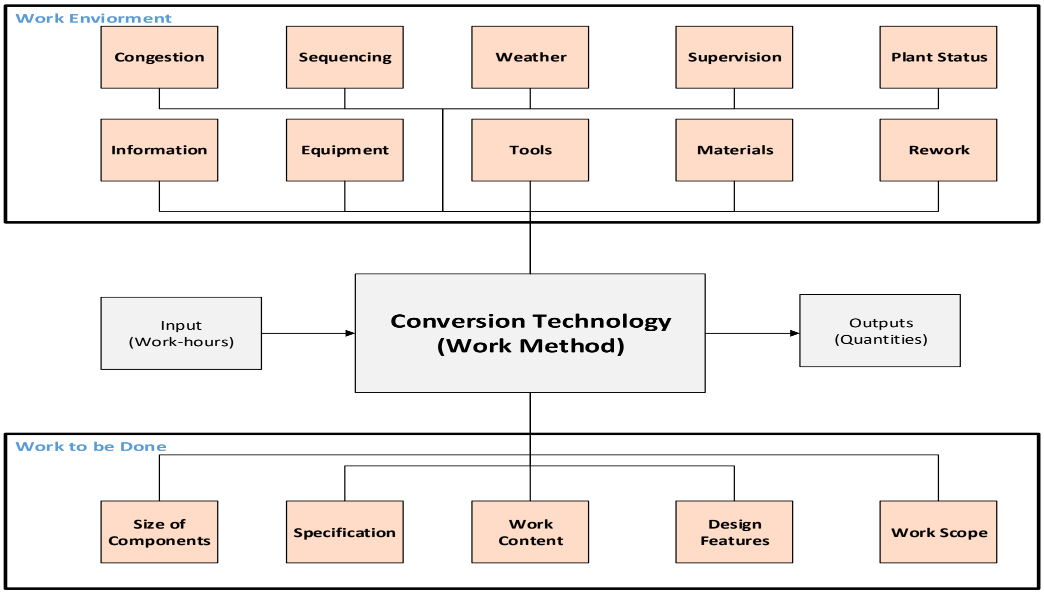


Figure 2-6. Factor Model of Construction Labor Productivity (Goodrum and Haas, 2002).

There is no standard definition of productivity. In some cases, productivity can be quantified (Equation 2.7) by dividing the units of work produced or completed by the corresponding man-hours spent (Ghoddousi and Hosseini, 2012):

$$Productivity = \frac{Completed\ or\ produced\ units}{corresponding\ time\ of\ workers} \qquad Equation\ 2.7$$

The unit rate is another concept that is commonly used along with productivity. A unit rate is estimated by dividing labor costs or man-hours per output over a predetermined period of time. Contractors frequently focus on the performance factor (Equation 2.8) to measure productivity (Schwartzkopf, 2004):

$$Performance\ Factor = \frac{Estimated\ Unit\ Rate}{Actual\ Unit\ Rate} \qquad Equation\ 2.8$$

Khan (2005) offered four different viewpoints towards a definition of productivity in the construction project industry: 1) Client Approach: This approach focuses on the value earned for the dollars used. This method neglects other key factors affecting productivity such as time and site conditions; 2) Designer Approach: The designer’s perspective defines productivity in terms of the required man-hours to deliver a specific task. This approach suffers from oversight of two major players in a construction project, namely, the cost factor and design quality; 3) Contractor Approach: Productivity should be defined as the output of some type of equipment or as the workforce needed to complete a unit of construction (according to the contractor's perspective); and 4) Labor Approach: Here, productivity is considered as depletions and ineffectiveness on the job.

2.3.2 Measuring Productivity in the Construction Industry

Most project control systems provide a mechanism that allows contractors and clients to measure either their project productivity or some surrogates for productivity; project control systems allow on-the-job monitoring of actual productivity as compared to projected productivity. Many contractors measure productivity in the form of a unit rate, either in dollars or man-hours. Determining the unit rate is considered a surrogate measure of productivity.

This approach for measuring productivity has some major drawbacks, some of which are listed below (Schwartzkopf, 2004): The working code is subject to misinterpretation; Accurate work hour tracking is not possible if the units are defined too narrowly or too broadly; and Error probability is very high if there is not a robust system for capturing data at the site level. It is very important to have a clear understanding of what productivity is so that contractors and clients can accurately measure it. The following section covers the methods widely used for measuring productivity in construction projects.

2.3.2.1 Direct Methods (DM)

There are two DMs for measuring productivity in the construction industry, the percentage of work units completed, and the physical units of work completed. The percentage of work units completed is a straightforward approach in which productivity is measured periodically for each work item in the form of the percentage of work completed. This method, however, does have some major drawbacks. Firstly, this method does not take into account that changes are generally imposed during the course of a project. Secondly, the process of defining the percentage completed is very subjective. Using the physical units of work completed is considered a more accurate approach.

The amount of material installed is counted from time to time. Thus, this method incorporates the variations or changes in the scope of work quantities that occur as a project progress. Similar to the percentage of work unit method, this approach is subjective in how the value on partly accomplished work items is determined. The major drawback of this method is that it requires an enormous amount of manpower and effort to track the number of units installed at the site level (Schwartzkopf, 2004).

2.3.2.2 Work Sampling (WS)

WS is a technique that captures the time that a workforce spends in various categories of activities, such as direct work, transporting materials, or an idle time (Thomas, 1991). Unlike DM, WS does not require an extensive amount of effort. A considerable number of observations are made to quantify what the workers are accomplishing at any point in time. The percentage of observations that shows that the labor force is really performing actual work is the percentage of time that is productive. Applying this method to construction projects requires a very good understanding of what direct work actually comprises, as construction activities fall into three areas (Schwartzkopf, 2004): Direct work: Everyday activities that are directly related to the actual work in process, such as picking up tools, holding material in place, housekeeping, etc.; Support Work: Everyday activities that are indirectly related to the actual work being done, such as planning, giving instructions, supervision, etc.; and Delays: All the time in a scheduled workday when neither direct nor support work is being done, such as personal time, late start, early quitting times, etc. It should be noted that work sampling is an indirect indicator of productivity because the time spent on direct work does not represent a high unit rate level of productivity (Schwartzkopf, 2004).

2.3.2.3 Craftsman Questionnaire Sampling (CQS)

The CQS method was developed to measure performance and was designed with the goal of improving productivity. In this method, relevant data is gathered using questionnaires. This method provides information regarding the source of delays and the amount of rework done, while also encouraging the participation of the skilled workers on site. The CQS approach has similar procedures to those of WS. Craftsman is selected randomly to provide information regarding activities that have just occurred. CQS, thus, has some advantages (Chang and Borcherding, 1986), as it: (a) utilizes the theory of binomial distribution to assessment ratio delays, (b) maintains the benefits of relative straightforwardness, and (c) maintains statistical reliability. It is worth mentioning that CQS does not estimate productivity directly and does not provide direct information regarding the unit rate or output per unit of work.

2.3.2.4 Five-Minute Rating (FMR)

The FMR method also involves collecting samples but does not follow the same statistical principles as WS or CQS. FMR provides valuable information regarding the magnitude of a project's delays and the effectiveness of its crew. The time required for observing a crew is proportional to the number of men in the crew but should not be less than five minutes. The total observation period is divided into intervals to monitor the performance of individual crewmembers. Each tradesman involved in some form of direct work for more than 50% of that specific time interval will be credited for the work completed in that time. At the end, the ratio between the credits achieved and the total possible credit represent each worker's efficiency (Thomas and Daily, 1983).

2.3.2.5 Group Timing Technique (GTT)

GTT is another sampling technique for construction project evaluation. GTT uses crewmember observations at a static time interval; these observations are categorized based on pre-set work cycle elements. This technique is suitable for highly repetitive and cyclic work. A full description of this technique can be found in "Crew Performance Measurement via Activity Sampling" by Thomas and Daily (1983).

2.3.2.6 Historical Data and References

There are several published standard labor productivity rates for estimating costs, budgeting, and scheduling. The following sources are widely used in the construction industry (Khan, 2005): RS Means – Building Construction Cost Data (US & Canada); Lansdowne's Construction Cost Handbook (Canada); Hanscomb's Yardsticks for Costing (Canada); and Craftsman's Building Cost File (US & Partially Canada). Although the above-mentioned manuals are valuable sources for productivity construction practitioners, some shortcomings are associated with them. Goodrum and Haas (2002) state that using solely the manuals may lead to overestimating construction costs. Despite the drawbacks associated with these manuals, there is still a preference for utilizing estimation manuals as a basis for predicting productivity levels.

2.3.2.7 Other Methods

Several high-tech methods have been utilized over the past two decades to measure productivity. For instance, audio-visual (AV) methods have captured construction field operations for the purpose of productivity analysis and productivity improvement, training and safety purposes, to monitor weather impact, equipment performance, and to analyze claims (Abeid and Arditi, 2002). AV methods are not a substitute for physical observation methods, but a valid supplementary method for improving and documenting them as AV methods facilitate the gathering and evaluating of data. These methods provide a permanent record of a project's progress which may be very useful at a later stage (Noor, 1988). Kim et al. (2009) proposed a new system for onsite productivity measurement, Wireless Real-time Productivity measurement (WRITE). The developed system has some valuable features. Firstly, it does not disturb ongoing construction activities. Secondly, it provides a real-time measurement of construction labor productivity. Thirdly, the information collected can be shared by all project parties via the

Internet, regardless of time and distance. Xue et al. (2008) proposed a new technique for "Measuring Productivity of the Construction Industry in China by Using DEA-Based Malmquist Productivity Indices." The proposed method utilizes the Data Envelopment Analysis (DEA), a well-accepted management tool. Xue uses DEA to assess the efficiency of decision-making units (DMUs) and circumvents any functional specification to define the connections between inputs and outputs. Portas and Abourizk (1997) developed an ANN model to estimate construction productivity for concrete formwork installation activities. Their ANN system employs historical data and contributions from knowledgeable construction supervisors. A three-layered ANN with a fuzzy output structure was adopted as the most suitable model since a considerable amount of input was subjective. Productivity measurement can be classified into two major categories, Continuous Observations and Intermittent Observations. Table 2.4 highlights the advantages and disadvantages associated with these two categories.

Table 2-4. Pros and Cons of Productivity Measurement Methods (Noor, 1998).

Measurement Method	Advantages	Disadvantages
Continuous Observations	1. Accurate time inputs 2. Detailed data for analytical purposes	1. Laborious and expensive 2. Restrictive in the number of workers or work crews monitored
Intermittent Observations	1. Allows for the monitoring of many workers & work crews 2. Less resource-intensive than continuous observations	1. Prone to errors in the determination of true times 2. Productivity data is in an aggregated format

Both methods provide project participants with unbiased feedback regarding the efficiency of the process and the ability to rectify adverse situations. These methods are effective management tools to efficiently plan, coordinate, and monitor a project's execution plan. Productivity in the construction industry is defined by labor productivity. Thus, productivity improvement is assured when wasted efforts in the work process can be identified, minimized, and/or eliminated (AACE, 2004a).

2.3.3 Factors Affecting Productivity

A number of different interrelated factors affect construction labor productivity in any specific project. Many studies have illustrated the effect of an explicit factor on construction labor productivity, such as overtime, learning curves, and congestion, but there is a marked lack of comprehensive studies designed to show how various interrelated factors affect construction labor productivity simultaneously. Even though many studies on identifying and evaluating factors affecting construction labor productivity are available, no comprehensive study analyzing the loss of productivity due to the interaction between these factors has been conducted yet

(Jansma, 1998). Key factors affecting labor productivity have been proposed by different researchers in different studies. Leonard et al. (1998) performed a field investigation of over 18 months at Revay and Associates Limited of Montreal (a consulting firm specializing in construction claims). Change order impact on productivity was at the core of their research. Ninety cases from 57 different projects were selected, cases where the contractors had experienced a considerable amount of change orders and the corresponding loss of productivity. Their study identified eight major factors that negatively affect productivity, including: the timing of the individual change orders, the type of work, interdependencies among trades, the intensity of the work, the frequency of design errors and omissions, contractor's management skill, and a lack of architect and engineer supervision. The frequency (as a percentage of the overall time) of how often these factors occurred was determined and is shown in Figure 2.7 (Leonard et al. 1988). Thomas (1992) studied the effects of planned or extended overtime on labor productivity. Planned or extended overtime is overtime that lasts longer than several weeks. Spot overtimes were excluded because their negative impacts are insignificant when compared to the scope of the work. Extended overtime can be characterized as a period of more than 40 hours of work per week that lasts for a minimum of three consecutive weeks. Thomas (1992) found that data sources were limited in the field, with many articles and publications citing other sources while offering no new data or vision. Productivity loss is a function of the number of hours per day and the number of days per week. Thomas concluded that the studies which show that productivity is not correlated to the numbers of hours per day and number of days per week are inconsistent.

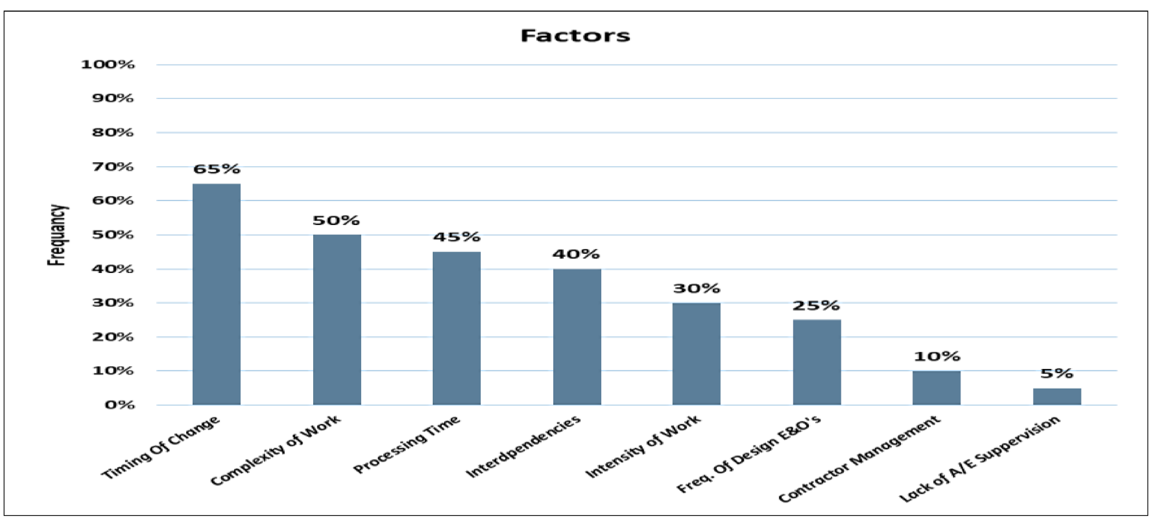


Figure 2-7. Factors Influencing Productivity Losses (Leonard et al., 1988).

Hanna and Heale (1994) conducted a survey to determine the factors affecting construction productivity across Canada. Their research focused on the dissimilarities between

Newfoundland and the rest of Canada. They identified and classified major productivity factors into six groups: contract environment, planning, site management, working conditions, working hours, motivation, and other factors. The following interesting conclusions are based on Hanna and Heale's (1994) study: 1) Critical plan method (CPM) planning and scheduling techniques have a positive impact on productivity; 2) Fixed-price contracts are more productive, while lowest-bid contracts have a negative impact on productivity; 3) Among site management factors, availability of issued for construction (IFC) drawings has the greatest effect on productivity; and 4) Occasional overtime may have a positive effect on productivity, whereas planned overtime and shift work has adverse impacts on productivity. Hana and Heale (1994) indicated that site management factors have an undesirable influence on labor productivity. Thus, mitigating the negative influence of these factors may result in productivity improvement. Makulsawatudom et al. (2004) focused on factors affecting labor productivity in Thailand, where the construction industry has experienced productivity difficulties. They distributed a structured questionnaire to 34 project managers actively involved in the Thai construction industry. The factors were ranked according to their level of influence and potential productivity improvement. To reinforce the data collected from the questionnaire, comprehensive interviews were performed with project managers. 23 factors in total affecting labor productivity were gathered and ranked, as shown in Table 2.5 (Makulsawatudom et al., 2004). Where CFI is critical factor index, and RII is relative importance index.

Table 2-5. Factors Affecting Construction Labor Productivity (Makulsawatudom et al., 2004).

Rank	Factors	Total CFI Score	RII
1	Lack of Material	358	0.405
2	Incomplete Drawings	330	0.373
3	Incompetent Supervisors	329	0.372
4	Lack of Tools and Equipment	309	0.350
5	Absenteeism	307	0.347
6	Poor Communication	301	0.340
7	Instruction Time	299	0.338
8	Poor Site Layout	298	0.337
9	Inspection Delay	294	0.333
10	Rework	291	0.329
11	Occasional Working Overtime	266	0.301
12	Change orders	265	0.300
13	Tools and Equipment Breakdown	261	0.295
14	Specification and Standardization	261	0.295
15	Interference from Other Trades and Another Crewmember	245	0.277
16	Workers Turnover and Changing Crewmembers	233	0.264
17	Scheduled Working Overtime	226	0.256
18	Safety Incidents	220	0.249
19	Poor Site Conditions	207	0.234
20	Changing of Foremen	204	0.231

Ghoddousi and Hosseini (2012) conducted a survey to identify the factors that affect the productivity of construction projects in Iran. They claimed that the Iranian construction industry endeavored to take all the measures necessary to decrease costs as much as logically possible. Major portions of projects were assigned to sub-contractors because of the strong belief among contractors regarding the inefficiency of a daily workforce. Their study aimed to identify the factors influencing sub-contractors' productivity by using a structured questionnaire. Thirty-one factors were identified and classified into seven broad categories. Table 2.6 shows 25 out of 31 variables.

Table 2-6. Ranking the Defined Groups and Their Factors (Ghoddousi and Hosseini, 2012).

1. Material/Tools	**Rank**
Materials not delivered onsite when expected	1
A shortage of a material in the market	2
Lack of proper tools and equipment onsite	3
Frequent tools/equipment breakdowns due to aging or poor maintenance	4
2. Method/Technology	**Rank**
Operatives do not have the skills and experience to perform the task	1
Use of traditional construction methods instead of modern technology	2
Company executing project type for the first time	3
Site is slippery or steep, imposing terrible working conditions	4
3. Management/Planning	**Rank**
No construction planning or project schedule in place	1
Tasks are not properly planned or realistically sequenced	2
Skilled workers are not adequate on jobs	3
Congestion and overcrowding on the site/interference among people working on the Jobsite	4
4. Supervision	**Rank**
Site manager does not have the ability to train workers to perform their jobs properly	1
Stoppages because of inspection delays	2
Work and break frequencies and durations are not properly organized	3
The site manager is not experienced enough to handle challenges that arise in the field	4
5. Reworks	**Rank**
Work needs to be redone due to damage after the work was complete	1
Work needs to be redone because it fails quality control inspection or testing	2
Fabrication errors require correction in rework	3
Work needs to be redone frequently due to the poor quality of documents, drawings or specifications	4
6. Weather	**Rank**
The thermal environment is not conducive to physical work (i.e. heat, cold, humidity)	1
7. Jobsite Condition	**Rank**
Inadequate water coolers and toilets, and/or no convenience store or covered rest area onsite or in the vicinity of the active workforce	1
The worksite is a considerable distance from homes or housing site	2
Jobsite is too noisy/dusty	3
Low level of lighting/poor ventilation/poor housekeeping/limited entrances	4

They focused on sub-contractor managers and their perceptions regarding the 31 factors' degree of influence on productivity on a time-based criterion. They found ten main factors adversely affecting labor productivity in descending order as follows: 1) Use of traditional instead of high tech construction methods; 2) Site managers that are not knowledgeable regarding issues that arise in the field; 3) Lack of proper tools and equipment on site; 4) Operatives do not have the abilities and experience to perform their task; 5) Site managers are not skilled in training workers to perform their jobs properly; 6) Lack of the required materials in the market; 7) It is the first time a company is executing a particular type of project; 8) Materials do not arrive on site when they are needed; 9) Thermal environment is not comfortable (i.e. heat, cold, humidity); and 10) Tasks are not properly planned or realistically sequenced. It can be concluded that the majority of the most influential factors are all finance-related, reflecting the financial problems imposed on Iranian construction companies by government irregularities in making payments during the course of projects (Ghoddousi and Hosseini, 2012).

Jarkas and Bitar (2012) concluded that the Kuwaiti construction industry suffers from low productivity. Using a structured questionnaire, they identified and ranked the relative importance of factors influencing labor productivity on construction projects in Kuwait. Their questionnaire identified 45 factors grouped into four primary groups as follows: (1) management; (2) technological; (3) human/labor; and (4) external. Ten of the 45 factors were recognized as having the most influence on labor productivity: 1) Clarity of technical specifications; 2) Extent of variation/change orders during a project's execution; 3) Level of coordination among the design disciplines; 4) Lack of labor supervision; 5) Proportion of work subcontracted; 6) Complexity of project design; 7) Lack of an incentive scheme to reduce costs; 8) Inadequate construction manager leadership; 9) Stringent inspection by the engineer; and10) Delays in responding to requests for information. Their research indicates constructability is the prominent concept affecting labor productivity in Kuwait. However, there is a lack of knowledge of constructability practices among construction practitioners in Kuwait. Hafez et al. (2014) performed a similar study in Egypt to identify and rank the critical factors affecting construction labor productivity. They identified 27 productivity factors and classified them into the following four groups: (a) technological, (b) management, (c) human/labor, and (d) external. Ten factors were shown to have the most significant negative impact on labor productivity: (1) payment delay, (2) poor labor skills, (3) shortage of experienced labor, (4) lack of labor supervision, (5) poor labor motivation, (6) overtime work, (7) lack of leadership skills among construction managers, (8) high humidity, (9) unclear technical specifications, and (10) high or low temperatures. The results of the abovementioned research are consistent with the results of similar research efforts carried out in Kuwait, Iran, and Thailand (Jarkas and Bitar, 2012; Ghoddousi and Hosseini, 2012; Makulsawatudom et al., 2004), and are very similar to the results reached in the Gaza Strip (Enshassi et al., 2009). It is clear that several known and existing factors influence construction labor productivity. Good planning and identification of these factors can mitigate their adverse impact. Using a novel holistic dynamic model in conjunction with a sound visualization tool could result in early identification, reduction, or elimination of these factors, thereby leading to an improvement in productivity.

2.3.4 Loss of Productivity

Loss of productivity may occur when construction labor productivity is impacted by events that a contractor does not have any kind of control over; hence, the contractor may be entitled to additional compensation. Loss of productivity claims creates exceptional challenges for the claimant who declares them and the defendant who defends themselves or their company against them. Inefficiency can be caused by various events and project parities, which means that determining loss of productivity attributable to a discrete event can be very problematic (Klanac and Nelson, 2004). The AACE list of the difficulties associated with the measurement and allocation of responsibility for losses in productivity includes the following (AACE, 2004b): 1) The events that cause a loss of productivity that an owner is held accountable for may not be easily detected at the beginning, unless a contractor is capable of monitoring productivity effectively and consistently from the early stage of a project's execution. If written notice is not given to the client in a timely fashion, then the integrity of the loss of productivity claims becomes debatable (AACE, 2004b); 2) Real-time tracking of productivity in construction projects is difficult if not impossible, unless a contractor employs some sort of structured Earned Value Analysis (EVA) for tracking productivity. Thus, validating productivity losses with the degree of confidence requested by clients may be very difficult (AACE, 2004b); 3) Too-often, productivity losses are calculated after the fact. In other words, they are not assessed proactively. Losses are usually quantified during a claim preparation or a request for equitable adjustment. Thus, every so often a lump sum estimate can be prepared for productivity loss claims (AACE, 2004b); 4) Some methods may result in fault-prone results and thus are not reproducible. These methods are therefore unreliable. It is quite possible that two methods will produce two different results that cannot be easily understood nor reconciled (AACE, 2004b); and 5) Establishing lost productivity causation(s) is challenging because contractors attempt to show that any losses are caused by clients (ex., due to change orders) and ask to be reimbursed. In contrast, clients try to justify lost productivity by using an inadequate or misleading bid process or by poor planning.

These two standpoints towards productivity issues in construction projects create a vicious cycle (AACE, 2004b).

2.3.5 Methods in Estimating Loss of Productivity

Quantifying loss of productivity in construction projects requires detailed answers to questions about many subjective assumptions on the part of contractors or claims analysts. Although the loss of productivity claims have been an attractive topic among professionals from industry and academia, no one-size-fits-all technique exists. Meanwhile, some widely accepted techniques, like the Measure Mile Analysis (MMA), rarely produce consistent results. Cost overrun due to loss of labor productivity is very difficult to assess; industry guidelines such as the National Electrical Contractors Association (NECA, 1976), the US Army Corps of Engineers (USACE, 1979), and the Mechanical Contractors Association of America (MCAA, 1986) can be used as sources for estimating productivity loss. However, these guidelines are prepared by an organization that advocates for one side of a conflict, with an expectation of financial gain and often with an unclear research methodology (Ibbs and Liu, 2005b). There are, however, some methods available to measure the loss of productivity due to change orders and other events that occur during the course of a project, but these methods do not highlight what factor(s) are the major contributor to productivity loss.

Lee (2007) classified these methods into three categories: traditional methods, statistical studies and models, and other methods. All of the existing methods currently available for assessing the loss of productivity, from traditional methods to more advanced ones that depend on newer approaches, are reviewed in the following sub-sections. Traditional methods include MMA, Total Cost Method (TCM), Modified Total Cost Method (MTCM), Jury Verdict Method (JVM), EVA, and Industry Indices and Studies. It should be noted that some of these methods have been criticized due to their lack of consistency and precision. On the other hand, others are widely used among construction practitioners, such as the MMA. Although the MMA has been commonly used and accepted for loss of productivity claims presented in courts, it does have some shortcomings. Researchers have proposed several improvement techniques for this method. For example, Ibbs and Liu (2005b) proposed an improved MMA that determines its reference period utilizing objective criteria.

2.3.5.1 Measure Mile Analysis (MMA)

The MMA was first introduced by Zink in 1986. MMA involves an assessment of the contractor's productivity achieved in the course of an un-impacted period, compared to the contractor's productivity on a similar task during an impacted period (Equation, 2.9). The un-impacted period is also known as the reference period for productivity analysis on the same project and can be expressed as:

$$Loss\ of\ Productivity$$
$$= (Impacted\ rate - Reference\ rate)$$
$$* Number\ of\ units\ during\ impacted\ period \quad Eqution\ 2.9$$

However, it is possible to select a reference period from a different project that includes a similar type of work (Jones, 2001). The following guidelines should be taken into account when choosing an MMA (Loulakis and Santiago, 1999). First, the work accomplished during the reference period should be significantly comparable in type, nature, and difficulty to the impacted work. Secondly, the configuration of the skill level of the crews should be comparable. Three major steps should be followed for calculating loss of productivity using MMA (Zink, 1986): 1) Plot the actual man-hours spent on a project versus the percentage of work completed; 2) The first and last 10% should be removed from productivity data because they are related to “ramp-up” and “tail-out” and are not truly representative of the expected average productivity; and 3) A linear or non-linear portion of the productivity curve in the intermediate 80% that represents the un-impacted work period and the most efficient rate of progress must be identified. There are major drawbacks associated with this method. Firstly, the reference period productivity must be established based on a continuous un-impacted period, a period which is not always readily accessible. Secondly, identifying the references periods in the MMA is very subjective (Ibbs and Liu, 2005b). Thus, the success of loss productivity claims prepared utilizing MMA depends in large part on the reliability of the selected comparable periods (Ibbs and Liu, 2011). Thirdly, to quantify productivity losses using MMA, good productivity record booking is essential.

Ibbs and Liu (2010 and 2005b) proposed and an improved MMA utilizing the statistical clustering method to overcome the bias of determining reference periods and similar workdays. Ibbs (2011) published a list of MMA principles utilizing a logical process for formulating and presenting a sound MMA method to support contractors, clients, consultants, and other parties. These principles are MMA Analyst Characteristics, Impacted Period, Reference Period, Loss of Productivity Quantification, and Loss of Productivity Presentation. In 2000, Thomas and Sanvido introduced the baseline concept to improve some MMA shortcomings. The baseline period is defined as a period of time when the contractor reaches their best productivity; this period does not need to be a continuous period nor must it be purely un-impacted. In their method, the baseline duration should be 10% of a project’s duration. The baseline method has two advantages over the MMA: 1) A lower level of detail. The MMA requires a reference period free of any disruptions, while the baseline method does not; and 2) Can be used in cases where no MMA is achievable.

The major disadvantage is that determining exactly 10% of daily productivity is a subjective task and it is possible that this 10% may not represent the project's best productivity (Table 2.7). Thus, the MMA is one of the preferred methods for quantifying the loss of productivity in the construction industry. Although MMA is widely accepted in many courts and appeal boards, there are some concerns regarding its consistency and reliability (Ibbs, 2011).

Table 2-7. Comparison between the Measured Mile and Baseline Productivity (Lee, 2007).

Measured Mile	Baseline Period
Negative impacts should be limited to those caused solely by the owner	Does not need to be free of owner impacts
The measured mile period should be a continuous period	The baseline timeframe does not need to be a continuous period
Focused on finding periods where there are no owner-caused impacts	Focused on finding the best performance the contractor can achieve

2.3.5.2 Total Cost Method (TCM)

In quantifying the loss of productivity, some contractors prepare their cases by utilizing the TCM. This method is the most straightforward of the traditional methods for measuring productivity losses. Loss of productivity cost is calculated by subtracting the bid amount from the total cost of a project or by subtracting the total bid hours from the total hours billed and the result is multiplied by the average labor rate. This method has serious shortcomings in its assumptions. It assumes that the contractor does not contribute to the inefficiency problems in a project and that the bid estimate is 100% valid. In addition, the client is solely responsible for any inefficiencies, hence, all the cost overruns must be compensated by the client. In other words, this method does not distinguish between the various factors that cause damage. The variance between the actual cost and the bid cost for the entire project is presumed to be a combination of factors, all caused by the action or inaction of the other party. Courts and appeal boards are not very keen to accept this method due to the abovementioned assumptions. This method can only be presented in courts if all of the following four requirements are satisfied (Lee, 2007): Demonstrating actual losses precisely and directly is very difficult/impossible; Bid estimate is precise and detailed; There are real actual costs, and Contractor is not held accountable for cost overruns. TCM should be considered as the last resort for quantifying productivity loss impact cost. In other words, it may be useful to employ this method only when damages cannot be isolated or easily quantified based on a change-by-change or breach-by-breach basis and when there is not enough information available.

2.3.5.3 Modified Total Cost Method (MTCM)

MTCM utilizes the inherent simplicity of the TCM approach. However, MTCM attempts to demonstrate that cause and effect relationships exist between the cost overrun experienced by contractors and the action or inaction of other parties. Thus, the success of MTCM strongly depends on illustrating the cause and effect dynamics (Kelleher et al., 2014). The first step in quantifying damages using MTCM is to adjust the contractor's bid for any shortcomings disclosed during the course of a project. In the same way, any costs that cannot be accredited to the other party should be deducted. Although this method is more likely to be accepted by courts and appeal boards because it does not have the deficiencies of the TCM, the same four conditions must be met by the contractors (Lee, 2007).

2.3.5.4 Jury Verdict Method (JVM)

JVM can be applied in cases where the causation of damage has been validated but the amount of damages cannot be quantified with confidence (Jones, 2001). The use of the JVM depends on the nature of the claims; it is particularly useful where the loss of productivity damages cannot be quantified due to lack of information. In these situations, a jury verdict can be used to determine a realistic and reasonable compensation amount for damages. Three conditions should be met before selecting this approach (Lee, 2007): 1) Strong evidence of injury; 2) Lack of a more reliable method to estimate damages; and 3) Adequate proof for a fair and reasonable guesstimate of the damages. The JVM may be used with other available techniques to quantify damages, such as engineering estimates, estimated labor hours, industry studies, etc. It should be noted that MTCM and MMA provide better results for calculating inefficiencies than the JVM because they take into account the causation of productivity losses (Lee, 2007; Jones, 2001).

2.3.5.5 Earned Value Analysis (EVA)

EVA is a common technique to measure project performance. This method incorporates a project's scope, cost, and schedule performances to assess and measure overall project performance and progress (PMI, 2013). Because of the problems with accurately measuring productivity, productivity measurement can be performed using EVA. In addition, EVA can be considered as a vehicle for measuring the loss of productivity by comparing the impacted and un-impacted Cost Performance Indexes (CPI). EVA is used as a surrogate for construction labor productivity. It should be noted that the accuracy of data could be jeopardized if the loading resources are not modified according to the changes imposed during the course of a project (Schwartzkopf, 2004).

2.3.5.6 Industry Indices

There are some industry indices available for quantifying productivity losses caused by change orders or other factors triggered by management policies toward change orders. Contractors and owners publish various manuals for quantifying the loss of productivity due to different factors. These manuals do not take into account any interdependencies among factors or utilize several factors for the same work (Ibbs and Vaughan, 2012). The following three guidelines are widely known among construction industry practitioners: i) MCAA Labor Estimating Manual (1994); ii) NECA Manual of Labor Units; and iii) USACE Modification Impact Evaluation Guide. The MCAA is one of the more popular sources for quantifying lost productivity. The manual provides the amount of productivity losses in the form of percentage for 16 factors that influence productivity (Lee, 2007). Table 2.8 shows a sample of MCAA (2016) factors that can have an effect on the project during the construction phase.

Table 2-8. Sample of MCAA Factors Affecting Productivity and Range of Losses (Lee, 2007).

Factor		Level of Condition		
		Minor	**Average**	**Severe**
1	Stacking of Trades	10%	20%	30%
2	Morale and Attitude	5%	15%	30%
3	Reassignment of Manpower	5%	10%	15%
4	Crew Size Inefficiency	10%	20%	30%
5	Concurrent Operations	5%	15%	25%
6	Dilution of Supervision	10%	15%	25%
7	Learning Curve	5%	15%	30%
8	Errors and Omissions	1%	3%	6%
9	Beneficial Occupancy	15%	25%	40%
10	Joint Occupancy	5%	12%	20%

Ibbs and Vaughan (2012) state the advantages and disadvantages of MCAA manuals in their "Change and the Loss of Productivity in Construction: A Field Guide." The key advantages of the MCAA manual are: 1) It is easy to use and apply because of clear and concise data; 2) Data is generated based upon a group of experienced professionals; 3) No reference period is required to apply the manual's data; and 4) Several factors can be used to quantify the productivity loss if the effects are combined correctly. The main disadvantages of the MCAA manual are: 1) Data is developed subjectively; 2) Subjective judgment should be made by the users to determine the level of a condition; 3) Interdependencies among factors should be taken into account prior to applying multiple factors; and 4) Recognizing the impacted period of work may be problematic. Although it has some serious disadvantages, the MCAA manual has been used successfully to quantify productivity losses (Ibbs and Vaughan, 2012). In 1992, the NECA issued a manual similar to the MCAA's. According to Lee (2007), the contents of Table 2.9 have remained the same since 1976, although the NECA manual is updated occasionally. The table has four major categories: building type, working conditions, general contractor, and electrical contractor, and all the factors affecting labor productivity are grouped under one of these major categories. The factors are classified into five levels according to their severity and productivity losses are represented as percentages (Lee, 2007). The NECA manual's advantages are similar to those of the MCAA manual. The major disadvantages of using the NECA manual are as follows (Lee, 2007): 1) Unknown source of data; 2) Subjectivity in assessing the severity of each factor; 3) The interdependencies among factors are ignored; and 4) No clear distinction between applying factors only to the work impacted by changes or to the entire project.

According to Lee (2007), a strong drawback of the NECA manual is that many of the factors included in the table are not suitable for clarifying and measuring the effect of changes orders. For example, construction type and job location are known variables from the beginning of a project and are not factors that can be affected by change orders. Thus, the NECA manual is more useful for assessing productivity at the planning phase (Table 2.9) (NECA, 1974; NECA, 1976; NECA, 1992).

The USACE published the "Modification Impact Evaluation Guide" in 1979. The manual covers four typical factors that cause inefficiency on unchanged work resulting from change orders. These factors were identified as disruption, crowding, acceleration, and morale and are described below. In a disruption, the contractor plans a project in the form of sequential activities leading to the completion of the project. The experienced workforce knows how the planned activities relate to the successful completion of the project, creating a "job rhythm." Optimum productivity is achieved when there is good job rhythm. Any disruption to the job rhythm will influence workers on un-impacted and impacted work and may result in a loss of productivity.

According to the USACE, disruptions occur when "workers are prematurely moved from one assigned task to another." Figure 2.8 was developed based on the assumption of full worker productivity achievable in a maximum 8-hour shift. Figure 2.8 is more appropriate for the construction industry according to the USACE (1979). The claim is that construction workers are skilled enough to execute a variety of tasks and hence they only require being re-oriented for new tasks rather than gaining new skills.

Table 2-9. Factors Affecting Proactivity Based on the NECA Manual (Lee, 2007).

Variable Factors	Degree 1	1 Max. %	2 Max. %	3 Max. %	4 Max. %	Degree 5	5 Max. %
Building Type		**-5**	**5**	**10**	**20**		**30**
1. Construction	Standard	0	1	2	4	Special	6
2. Design	Simple	-1	1	2	4	Elaborate	6
3. Floor Plan	Uniform	-1	0	1	2	Complex	5
4. Occupancy Use	Usual	-1	0	1	1	Special	3
5. Size - Floor Area	Small	-1	0	1	1	Large	2
6. Extent of Elec. System	High Dens.	0	1	1	2	Low Dens.	3
7. Design of Elec. System	Simple	-1	1	1	2	Complex	3
8. Quality of Elec. Layout	Excellent	-1	0	0	1	Poor	2
Working Conditions		**-5**	**3**	**10**	**20**		**30**
1. Job Location	Close in	-1	0	1	2	Out of Town	3
2. Weather	Excellent	0	1	2	4	Extremely Bad	6
3. Working Space	Large Clear	-1	0	1	2	Small Clutter	3
4. Amount of Work by Other Trades	Very Little	-1	0	1	2	Very Congest	3
5. Material Storage	Excellent	-1	0	1	2	None	3
6. Shop and Bench Space	Excellent	0	1	2	4	None	6
7. Material Hoisting Conditions	Excellent	-1	1	2	4	None	6
General Contractor		**-5**	**5**	**10**	**20**		**30**
1. Experience with Work	Considerable	-1	1	2	4	None	6
2. Progress Maintained	Excellent	-2	2	4	8	Poor	12
3. Coordinate Trades	Excellent	-2	2	4	8	Poor	12
Electrical Contractor		**-5**	**5**	**10**	**20**		**30**
1. Experience	Considerable	-1	1	2	4	None	6
2. Experienced Supervision	Available	-2	2	4	8	None	12
3. Experienced Workers	100% Available	-2	2	4	8	None	6
4. Adequate Tools & Eq.	Adequate	-1	1	2	4	None	6

However, it is difficult to justify using Figure 2.8 instead of a learning curve for quantifying disruption-related productivity loss (Lee, 2007). The learning curve's effect on productivity is discussed in the model boundary chapter. The second typical factor that causes inefficiency on unchanged work resulting from change orders is crowding. If the contractor's schedule is altered due to change orders, more activities may need to be accomplished simultaneously.

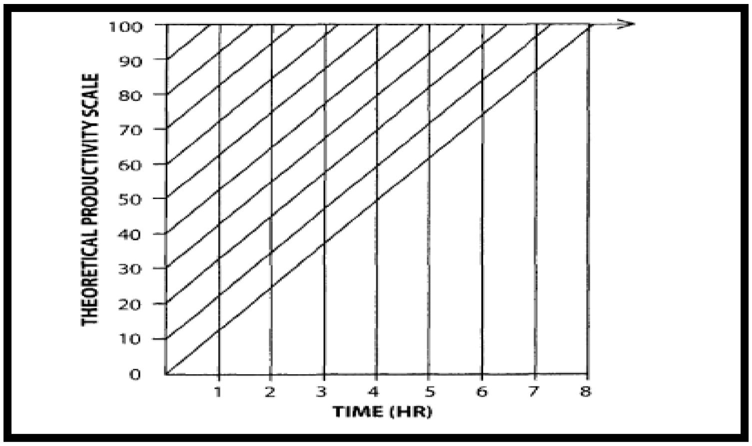


Figure 2-8. Const. Operations Orientation/Learning Chart (USACE, 1979).

Crowding will occur when more workers are assigned to a given area than can function efficiently in that space. USACE (1979) report provides a graph for quantifying the loss of productivity due to crowding (Figure 2.9).

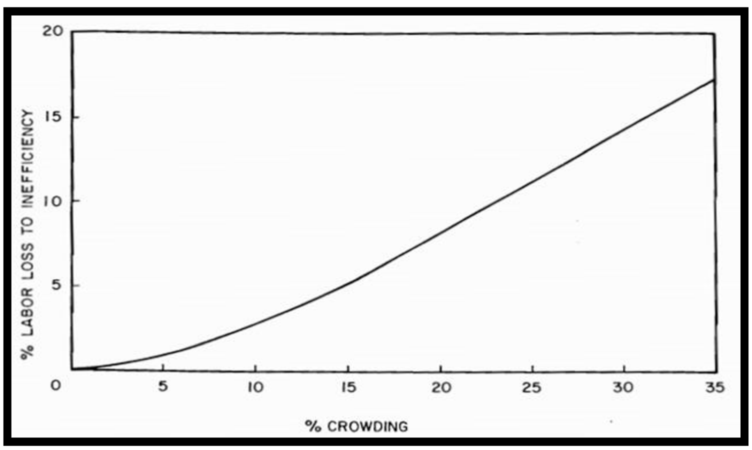


Figure 2-9. Effect of Crowding on Productivity (USACE, 1979).

The third factor is acceleration. Acceleration will occur when change orders require contractors to deliver more work during the same timeframe even though they may be entitled to a time extension. The report identifies three types of acceleration as follows:

- Increasing the size of crews;
- Increasing shift lengths and/or days worked per week; and
- Multiple shifts.

The three types of acceleration are introduced and discussed in the model boundary chapter.

The last factor that causes inefficiency on unchanged work resulting from change orders is morale. The NECA report states that the contractor is responsible for keeping the workforce motivated and furnishing a psychological environment that encourages striving for optimum productivity. Although a large number of changes or change orders has a negative impact on workforce morale, quantifying the impact of morale on productivity is not possible as it requires assessing morale. However, sufficient attention should be given to workforce morale because it plays an important role in productivity (Lee, 2007).

2.3.6. Reliability of Traditional Methods

These methods are classified into three major groups: project practice-based, industry-based, and cost-based methods. The level of effort and judicial acceptance generally increases as those methods with more and more certainty are employed. Figure 2.10 shows the relationship between the levels of required documentation, required verifiability of project data, consistency of methods, and the cost and proficiency of recording, preparing, and documenting the quantum of damages (Ibbs et al., 2007).

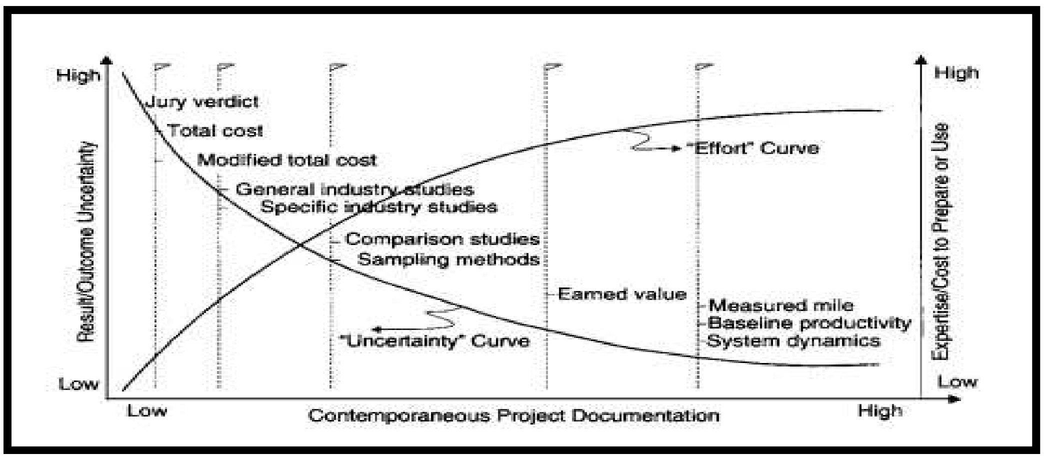


Figure 2-10. Reliability of Lost Productivity Quantifying Methods (Ibbs et al., 2007).

Expertise, cost, and effort will increase left to right. While the level of real-time project documentation will increase as more detailed methods are employed on the horizontal axis (Ibbs et al., 2007). The MCAA manual has been adopted and received fairly positively as compared to the two other studies, the NCAA and the USACE manuals, which have been widely rejected (Lee, 2007). TCM and MTCM have not been broadly recognized due to the uncertainty of their results.

2.3.7 Previous Researches for Quantifying Loss of Productivity

There are several methods and techniques developed by researchers to quantify the loss of productivity. Table 2.10 presents a summary of the most prominent researches as well as recent studies that were conducted by previous researchers in chronological order. The information in the table below only considers the reliable studies that provided useful and valuable information.

Table 2-10. Summary of Previous Research for Quantifying Loss of Productivity.

Author(s)	Year	Remarks
Leonard	1988	Data were taken from 90 projects that were in the dispute phase. Curves were developed to show productivity loss to the amount of change. Applicable to electrical/mechanical work, civil/architectural work, and combined work of all kinds as well as commercial/institutional building construction and industrial construction.
Hanna et al.	1999a	Two models were developed for electrical trade and one for the mechanical trade (Commercial, institutional, industrial, and residential projects).
Hanna et al.	1999b	A logistic impact model for predicting the probability of a project being impacted by changes and a linear regression model that predicts productivity loss for impacted projects.
Lee et al.	2004	A decision tree approach to classifying and quantify the cumulative impact of changes.
Ibbs	2005	Applicable to heavy/highway, commercial, and industrial projects. A regression model for plotting the cumulative changes of the project in question according to the % complete and compare the curve with the three given curves. Choose the closest curve for application, whether early, normal, or late change curve. The productivity index can then be read from the given graph or calculated using the equations
Moselhi et al.	2005	A neural network for quantifying change orders impact on labor productivity. One improvement is the consideration of the timing impact of change orders.
Hanna et al.	2008	A study shows the positive and negative impact of shiftwork. Productivity can be improved by 11% due to proper utilization of shiftwork. However, loss of productivity can be experienced due to shift work can reach 17% depending on the amount of shiftwork used
Al-Kofahi	2016	A system dynamics model was developed to qualitatively measure the impact of the change in the project scope on labor productivity. The model is analyzed using different road construction projects.
Moayeri et al.	2017	A BIM-based model was developed to capture the ripple effect of the owner requested design changes. The model calculates the impact of design changes and their ripple effect on a project's total duration.
Hanna & Iskandar	2017	A regression model that predicates the cumulative impact of changes for electrical and mechanical construction projects. Sixty-eight impacted projects were used in order to quantify the cumulative impact of changes using linear regression analysis.
Emamifar	2019	Two cascade neural network models are developed for quantifying the loss of productivity due to change orders, timing and without timing models. 9 variables were considered in developing without timing model and timing model consist of three sub-models, namely as early, normal, and late changes.

2.4 General Overview of SD Modeling Simulation

The terms model, system, and dynamic are key components of this research's definition of simulation. Before explaining the SD Modeling Simulation, it is vital that the three terms used extensively throughout this research be clearly defined. What the system does mean in the simulation spectrum. A system is defined as "An organized, purposeful structure that consists of interrelated and interdependent elements (components, entities, factors, members, parts etc.). These elements continually influence one another (directly and indirectly) to maintain their own activity and the existence of the system, in order to achieve the goal of the system (Business Dictionary, 2015)." Shannon (1998) defines a system as a collection of interconnected elements that work together to achieve a specific objective. A system can be viewed as a set of interconnected procedures, actions, and practices developed to serve a specific task based on the regulations and policies (external inputs) of that system. A system is described by the set of variables at a specified point in time that is called the "state", and its behavior is determined by the states of the critical variables. Meanwhile, a model is an abstraction of a group of objects, ideas, or real-world situations and offers a platform within which a particular situation can be examined and scrutinized (Ford and Sterman, 1998; Pritsker and O'Reilly, 1999). Models provide information that supports the decision-making process when interpreted according to certain rules or conventions (Zayed and Halpin, 2001). In this research, dynamics is understood as the study of how a system or an element changes over time. The construction project environment is dynamic and relatively unstable, both internally and externally (Love et al., 2002). A construction project may experience changes during its lifecycle and these changes may have substantial and volatile impacts on a project's outcome. Simulation is defined as "the process of designing a model of a real system and conducting experiments with this model for the purposes of either understanding the behavior of the system or of evaluating certain strategies (within the limits imposed by a criterion or set of criteria) for the operation of the system" (Shannon, 1975). Simulation is often used to evaluate a set of predefined options; it does not produce optimum solutions for a system (Oloufa, 1993). Although the application of analytical techniques is more desirable than creating a simulation, the majority of practical systems are too complicated to model by mathematical techniques. Thus, simulation modeling may be used to mimic real system behavior without the substantial cost associated with real situational experiments (Oloufa, 1993). The most important step in the simulation process is to develop a reliable simulation model that can function as a surrogate of the system under study. The model should be verified and validated to ensure accuracy of the simulation runs. Simulation models can be classified into three categories: discrete, continuous, and hybrid. Discrete simulation behavior is shown in Figure 2.11a. Continuous simulation behavior is observed constantly over time. This is performed according to a set of differential equations (Figure 2.11b). In a hybrid simulation, the change in the variables happens discretely, continuously, or continuously with discrete jumps over simulation time, as shown in Figure 2.11c (Pritsker and O'Reilly, 1999).

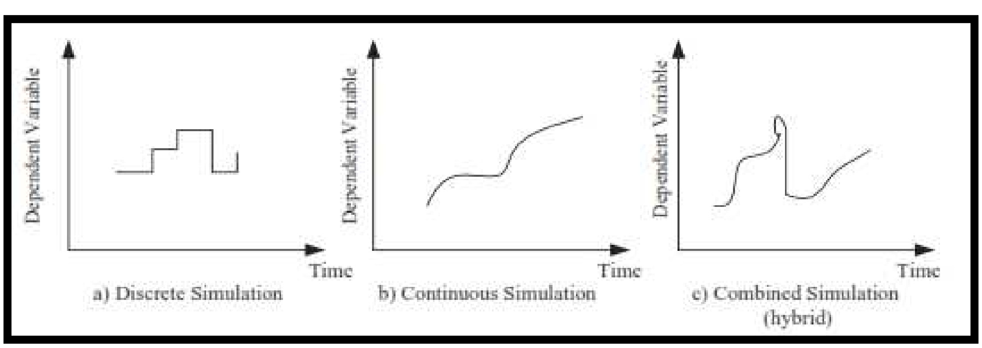


Figure 2-11. Simulation Modeling Techniques (Pritsker and O'Reilly, 1999).

In construction projects, the dependent variables at the operation level can occur discretely, continuously, or as a combination of both (Alzraiee, 2013). All the existing simulation models are governed by the nature of the problem being modeled and the preference of the modeler. In this research, SD simulation modeling is utilized to achieve the research objective. SD is a technique of analyzing how decisions, policies, structure, and delays are interconnected to influence the behavior of a system.

2.4.1 Strategic and Operational Project Management

Project management can be classified into two major approaches based on the main focus of construction project management: strategic project management and operational project management (Table 2.11). Strategic management can be viewed as a combination of quantitative and qualitative fields. The domains of operations, logistic, and finance have been formalized over the past decades by management and industrial science. The real difficulties arise when the human dimensions of psychology, sociology, and human resource management are combined with the quantitative part of strategic management. Together, the quantitative and qualitative components of strategic management address the various organization requirements, including professional, technical, and strategic demands (Chinowsky and Meredith, 2000). Strategic project management concentrates on a single project strategy, which may be positioned on the systems design and offers a foundation for defining the main objectives (Lee et al., 2006). Project level strategic decisions are part of "strategic project management [which] covers decisions that are taken upfront in designing the project, and then the guidance provided to operational decisions that consider the longer-term impact of these decisions on the downstream performance of the project" (Lyneis et al., 2001).

Table 2-11. Strategic and Operational Project Management Comparison (Schultz et al., 1987).

Viewpoint	Strategic Project Management	Operational Project Management
Level	Macro	Micro
Assessment	Subjective	Objective
Nature of problem	Understand, one at a time	Objective
Information needed	A small amount of specific information	A large amount of information
Planning horizon	Long-term but varies with the problem	Short-term and more constant
Frame	Covers entire scope of the project	Concerned only with sub-project units
Level of detail	Broad and general	Narrow and problem-specific
Evaluation	Difficult, because of generality	Easier, because of specificity
Perspective	Holistic and continuous	Reductive and discrete
Focus	Strategic/context	Operational

Operational project management is defined as "the management actions incorporated to meet a project's target by adjusting the time, cost, and resources" (Lee et al., 2006). The major differences between strategic and operational management are that operational management is based on discrete analysis and studies the effects of fluctuating time, cost, and resources in order to achieve the planned objectives (Lee et al., 2006).

2.4.2 Continuous Simulation

Continuous simulation is appropriate for systems wherein the variables can fluctuate continuously. In other words, the state of variables in a system changes continuously over time. Developing a solid causal loop diagram can be viewed as a foundational block for having a sound continuous simulation model. A causal loop diagram demonstrates the interactions among the variables in a system. Continuous simulations are based on a set of mathematical equations that describe the rate of change of variable state concerning time. Compared to discrete event simulation, continuous simulations are simpler to build and fewer data and data preparation is required (Helal, 2008). However, it should be noted that a mathematical representation of a complex system requires a tremendous amount of time and effort from the modeler.

2.4.3 The SD Simulation Approach

SD was introduced in 1965 by Forrester as a technique for modeling and scrutinizing the behavior of complex social systems in the industrial sector (Forrester, 1965; Forrester, 1968; Forrester, 1992). Traditionally, projects have been viewed as linear or as “static and closed”, proposing a hypothesis of firmly ordered projects that progress in well-defined, foreseeable stages to their completion. In the real world, projects are dynamic and adopt new plans during their course rather than adhering strictly to the initial one (Rodrigues and Bowers, 1996). SD is the appropriate tool for portraying the dynamic behavior of complex real-world systems where feedback loops and delays are present (Bakkila, 1996). SD has been utilized where a holistic view is essential and feedback loops are critical to understanding the interdependencies among the variables included in the system, such as those of social, economic, and environmental systems (Rodrigues and Bowers, 1996).

The solutions for many real-world problems lie in system thinking. System thinking is the ability to see the world as a complex system, where “everything is connected to everything else” (Sterman, 2002). The following attributes are common among complex systems, even though they are counterintuitive: Constantly Changing, Tightly Coupled, Governed by Feedback, Nonlinear, History-Dependent, Self-Organizing, Adaptive, Characterized by Trade-Offs, Counterintuitive, and Policy Resistant. SD modeling includes two core concepts: Causal Loop Diagrams (CLDs) that represent the conceptual relationships among variables in the system and Stocks-Flows Diagrams (SFDs) that describe changes in the variables' states over time (Randers, 1980).

2.4.4 The SD Modeling Process

The first step in developing an SD model is to outline the problem as clearly as possible by defining the conceptual model that shows the model addresses. It is recommended to begin with a very simple model because, at this point, important dynamics are still under investigation. As the size of a model increases, its complexity increases as well. The second step is to define the important variables; the model should have well-defined boundaries. All the important variables should be listed in this step. The third step is to develop CLDs to illustrate system feedback. Once the CLDs have been developed, a set of mathematical equations to define the interactions of the model variables can be constructed. The final step is to test the model by adding all the components into a computer simulation to evaluate its robustness. The modeling and procedures involved in constructing SD models are discussed in detail in the following section.

2.4.5 Overview of the SD Modeling Process

The SD method includes five major steps for modeling a system as follows (Sterman, 2000):

I. Problem Articulation (Boundary Selection): Considered the most important step, this is the foundational block of an SD model. To have a successful model, the modeler must have a clear understanding of the problem. A full understating of some models is often beyond human mental capabilities; therefore, it should be broken down into smaller systems without violating the holistic concept of SD. This step acts as the logical edge, providing the principles with which to choose what can be included or ignored in the model. In other words, all the essential features necessary for fulfilling the purpose of the model should be identified in this step.

II. Formulation of Dynamic Hypothesis: After the problem has been understood and characterized over a proper period, the modeler should identify the contemporary theories of the problematic behavior. A road map is developed here, based on the initial hypotheses, major variables, reference modes, and other available data utilizing: Model boundary diagrams; Subsystem diagrams; Causal loop diagrams; Stock and flow maps; Policy structure diagrams; and Other facilitation tools.

III. Formulation of a Simulation Model: This step covers the specification of the structure and decision rules. The estimations of variables, behavioral relationships, and initial conditions should be quantified at this stage.

IV. Testing: The model should be tested to assure its robustness. The developed model should be capable of satisfactorily mimicking the problem behavior and it should work accurately under extreme circumstances.

V. Policy Design and Evaluation: This step is where all the possible environmental conditions are anticipated and designed for. To show how the model behaves given uncertainty in parameters, initial conditions, model boundaries, and aggregation, a sensitivity analysis should be implemented in this step. In addition, a what-if analysis should be performed to show the effect of the different policies. It should be noted that this modeling is a feedback process (Figure 2.12) and not a linear sequence of steps (Sterman, 2000).

2.4.6 The Use of System Dynamics in the Construction Industry

Construction projects are challenging to manage and plan due to the projects' surrounding environments. Performance advancement over time is a result of feedback replies, many involving nonlinear interactions among key project variables and the accumulation of project progress and resources (Lyneis and Ford, 2007). Many simulation models have been developed to address project management issues in the construction industry by utilizing SD. SD models cover a variety of problems in the literature, ranging from simple models that address a single project to advanced models where a group of projects is represented in a single SD model.

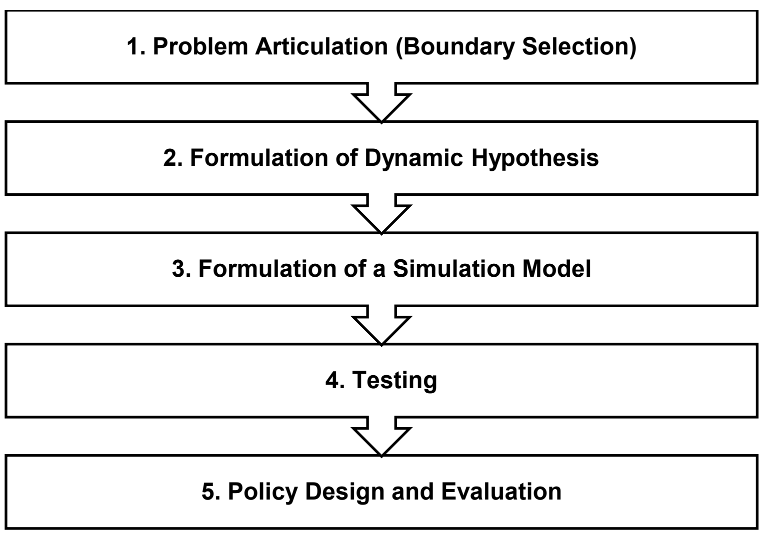


Figure 2-12. The Modeling Process is Iterative (Sterman, 2000).

This research focuses on single SD modeling and other approaches: AI and BIM. The SD models in the literature vary based on the level of detail included in the model structure descriptions, from comprehensive model disclosure to almost none (Lyneis and Ford, 2007). Forrester (1993) predicted that about 20 novel SD models would be proposed to cover 90% of the issues that may be faced by decision-makers in enterprises. Many of the SD models studied in this research were developed based on early Forrester models. SD modeling is a powerful tool that provides the mechanism for understanding the complex structure of project management issues in construction projects. By utilizing SD during the lifecycle of a project, SD can prove a great advantage in improving system performance. It should be noted that the complexity of SD models increases linearly. However, integrating a number of several simple SD models can lead to a holistic model for a much better understanding of a complex issue (Forrester, 1997).

SD modeling simulation emphasizes policy decisions included in the feedback loops rather than isolated decisions. Analyzing management decisions can be performed over longer time horizons without the difficulties of a minimum of available data. The SD models developed so far have covered the main project aspects, namely controlling feedback loops, ripple effects, knock-on effects, and the rework cycle (Cooper 1993a; Cooper 1993b; Cooper 1993c). Ripple and knock-on effect feedbacks are characterized by nonlinear relationships.

However, not enough research has been conducted on how the nature or the strength of these relationships might vary by project type (e.g. road construction vs. high-rise building construction) or how new techniques such as BIM can reduce the likelihood of error occurrence. In the following chapters, SD will be integrated with other techniques, including AI and BIM, and applied to a real case study.

The causal loop diagram and the resulting stock and flow dynamic model will be portrayed and assessed. System dynamics modeling has been utilized in many different fields of study, including project management, defense analysis, and health care. In construction, It has been used to describe the complex relationship of a series of events resulted in costly delay and disruption. System dynamics is a beneficial tool to deal with the dynamics' convolution shaped by the interdependencies, feedback, time delays, and nonlinearities in construction projects. Table 2.12 summarize previous SD studies in the construction industry.

2.5 Artificial Neural Network (ANN)

The use of ANN-based systems in the construction industry began as early as the late 1980s. ANNs are now appreciated as strong predictive tools for recognizing patterns among input variables and output(s). Introduced in the 1940s, they gained attention throughout the 1960s. However, due to learning limitations, the earliest type of ANN was only a single layer perceptron. More powerful multilayer perceptions, also known as back-propagation networks, gained popularity in the 1980s. NNs are able to draw the relationships between inputs and output(s); especially when it is difficult to build a linear or nonlinear mathematical relationship.

Table 2-12. Summary of Previous SD Study.

Authors	Year	Remarks
Love et al.	2002	An SD model to investigating the change and rework on project management performance. The model shows the usefulness of monitoring project dynamics and developing appropriate responses efficiently to changes within the project.
Howick and Eden	2001	An SD model was developed to represents the complexity of disruption and delay caused by earlier project delivery in an attempt to help managers and contractors in decision making. The impact of compressed delivery date on disruption & delay was assessed in relation to two specific and typical options: namely, pressure & overtime.
Howick	2005	This research discusses the experience of using SD models to backing claims for reimbursement for time and cost overruns on large and complex projects. This paper examines the nature of responses to SD models by litigation audiences. These reactions highlight issues that the modeler faces when constructing a model.
Eden et al.	2005	A comparison study to show the advantages of SD modeling over MMA in litigation. The study concludes that despite the popularity of the measured mile approach in litigation, its results can be untrustworthy in cases where disruptions and delays are a substantial part of the explanation for project late delivery and costs overruns.
Ibbs and Liu	2005a	An SD model is presented in this research as a tool that can show the relationship between cause and effect; that is, disruption/delay/acceleration and productivity loss.
Lee and Pena	2005	This research presents a SD model, which focuses on the dynamics of error and change management, including quality management, scope management, the request for information process, and the decision-making process for the approval of changes, and their consequent detrimental impacts on project performance.
Ibbs et al.	2007	A CLD that can be used when changes occurred in a construction project to illustrate the feedback loops among changes, disruptions, and loss of productivity.
Love et al.	2010	An SD model to show the impact of rework in oil and gas complex projects. The model attempts to show the relationship between factors that contribute to rework.
Alvanchi et al.	2012	An SD model for estimating the expected productivity in many different construction projects under the different arrangement of a working hour.
Nasirzadeh and Nojedehi	2013	An SD-based approach to model the complex inter-related structure of different factors affecting labor productivity is modeled using SD approach.
Warhoe	2013	A SD model was developed based on the works of several academics works as well as the contributions of several experts in the construction field. The model simulates the workflow of labor hours in a design-bid-build project.
Han et al.	2013	A model for showing that design errors are the main contributor to schedule delays in a university building project. Additionally, the case study revealed that schedule pressure spreads the negative impact of design errors on many other construction activities, even including those not directly impacted by the errors.
AL-Kofahi	2016	A SD model is developed using Vensim Software, validated, & utilized to quantitatively calculate the impact of the change in the project scope on labor productivity.

Moselhi et al. (1991b) was a pioneer in this domain and paved the road for other researchers by describing the potential applications of ANNs in construction engineering and management. Authors developed NNs for estimating optimum mark up. Moselhi (1991b) states, “Neural networks attempt to model the brain learning, thinking, storage, and retrieval of information, as well as associative recognition.” NN applications have covered a variety of construction areas, such as earth-moving equipment productivity, the effects of site environmental factors on labor productivity, and the productivity of concrete frameworks (Karshenas and Feng, 1992; Chao and Skibniewski, 1994; AbouRizk and Wales, 1997; Portas and AbouRizk, 1997, Golnaraghi et al., 2018; Golnaraghi et al. 2019). Quantifying productivity and the cost of construction under certain circumstances are popular topics for NN applications. Moselhi et al. (2005) developed a novel NN model capable of quantifying the impact of change orders on construction labor productivity. The function of finding a relationship between variables via NNs is known as the learning phase. The learning phase is controlled based on the error of the produced networks. The other NN function is called retrieval, which incorporates the inputs to a trained network and generates predictive responses. Training can be classified as either supervised or unsupervised. If the output is available in the data entry, the training is supervised. Else, it is considered unsupervised. Before considering the possibility of using NN for quantifying change order impacts, it is necessary to understand the basic principles of NN (Poole and Mackworth, 2010).

2.6 Building Information Model (BIM)

Over the past decade, considerable advancements have been made in the construction industry. These advancements were made possible by the introduction of BIM. BIM is defined as “a digital representation of the physical and functional characteristics of a facility. As such, it serves as a shared knowledge resource for information about a facility, forming a reliable basis for decisions during its lifecycle from inception onward (Smith and Edgar, 2008). The US General Services Administration (GSA) defines BIM as “the entire processes of exchanging, reusing, and controlling of information generated during the lifecycle of a building through an object-oriented artificial intelligent information model” (GSA, 2006).

The maturity level of BIM in an individual organization will influence that organization understands of BIM and its definition (Barlish and Sullivan, 2012). BIM is a powerful tool in the construction industry, one that can have a significant positive impact on productivity, efficiency, quality, and sustainable development. BIM is gaining the attention of construction industry practitioners, especially since major building owners such as the US GSA and the USACE require all projects involving the design and construction of facilities to include BIM (McCuen, 2008). The main goal of utilizing BIM is to have a holistic view of a building by encompassing the drawings, specifications, and details into a single-source computer platform (Krygiel et al., 2008). In addition, BIM is a powerful tool for illustrating the interdependences among building elements. BIM is much more than a database for developing models; it represents object-oriented building design. A major advantage of utilizing BIM in project development and execution phases is the ability to review the constructability of the design prior to beginning execution (Shourangiz et al., 2011). BIM can provide information about a single element or for all elements in a project. BIM facilitates the integration of disjointed practices and can act as the catalyst for changing business processes (Aranda-Mena et al., 2009). Khemlani (2007) performed a broad BIM survey that revealed that "The need for drawing production is still paramount, making this the top-ranking criterion for BIM solutions across all categories of firms and respondents." Projects that have effectively utilized BIM show numerous benefits over traditionally delivered projects, such as increased design quality, improved field productivity, cost predictability, reduced conflicts and changes, less rework, increased fabrication, and reduced construction cost and duration (Staub-French et al., 2011).

BIM can be utilized to support a variety of functions during the course of a project. Based on the reviewed literature (Azhar, 2011; Ashcraft, 2008; Foster, 2008; Kreider et al. 2010; Montaser, 2013; Moayeri et al., 2015), some of the various BIM applications described by researchers are Site Data Acquisition, Design reviews and design authoring, 3D control and planning, 4D modeling, site utilization planning, structural analysis, energy analysis, cost estimation, sustainability LEED evaluation, building system analysis, space management, and facility management. For example, Langroodi and Staub-French (2012) developed a change management system in the context of a multi-disciplinary collaborative BIM environment during the design and construction of a fast-track project. Utilizing BIM in the change management process provides easy access to changed data and can provide a comprehensive view of the ripple effects of changes.

A recent study carried out by the Stanford University Center for Integrated Facilities Engineering (CIFE) shows the benefits of BIM-based on 32 major projects (Gao and Fischer, 2008): Elimination of unbudgeted changes, up to 40%; Increased cost estimation accuracy; Decreased cost estimation process time, by up to 80%; Implementation of clash detection, leading to a saving of close to 10%; and reduction of overall project time of close to 7%. Applying BIM throughout a project lifecycle allows for more effective project management by reducing cost and time.

2.7 Findings, Limitations, and Research Gap

The broad literature review shows that there have been several efforts to qualitatively and/or quantitatively evaluate change order impacts in the construction industry using different tools and techniques. Construction projects can be classified into their strategic and operational phases, so developing a holistic simulation model must consider these management decisions at the appropriate strategic level and with their specific characteristics. SD modeling helps to portray a complex dynamic system with nonlinearly interacting variables. However, the SD model has certain limitations related to how it approaches a real complex problem. Integrating SD with other techniques, such as AI and BIM, can help overcome the shortcomings associated with SD. AI is utilized to improve the computational aspect of SD modeling simulation. As mentioned previously, SD requires a tremendous amount of mathematical equations to draw the relationships among variables. AI helps to recognize the pattern among nontangible variables and their impact on construction labor productivity. BIM improves the change management approach during the development phase, making it possible to visualize the changes and their impacts during that stage, thereby leading to early detection of the cumulative impact of changes. Adapting these tools for analyzing change order impact in construction projects needs more investigation, as construction projects are unique and involve many variable interactions. Looking at a variety of SD models found in the literature, several shortcomings of the current practices in quantifying productivity losses due to construction project change orders can be found. The review of the existing literature on change order management model shows that: i) The advantages of the existing methods for quantifying productivity loss due to change orders and other key variables have been well-argued and established. However, there is no comprehensive approach that can address multifaceted policies and the precise assessment of the impacts of changes in construction projects; ii) Although the area of SD simulation was introduced in construction modeling more than three decades ago, research in this area is not mature enough and is still in its initial stages; iii) The advancements in SD modeling originated in fields other than construction. This presents some hurdles for the applicability of SD modeling to the construction industry, where numerous variables interact to generate project behavior. Therefore, the uniqueness and complexity of the construction industry must be considered; iv) The methods and procedures initiated to quantify change order damages are one-dimensional and mainly after-the-fact approaches. This contradicts the objective of this research where both post hoc and contemporaneous approaches should be considered to address the problems that arise during the course of a project due to change orders and management policy. Given the above, it is clear that there is a need for an improved SD model aided by a novel AI method capable of identifying consequential changes as well as prioritizing elective changes throughout several construction project phases. The next chapter further draws on the gaps in existing research outlined here and proposes a methodology for developing an integrated change management model for estimating labor productivity loss due to change orders and managerial policies across all construction projects phases.

3. CHAPTER THREE: RESEARCH METHODOLOGY

3.1 Methodology Overview

This chapter presents a detailed description of the research methodology followed to achieve the research objectives. The methodology, as demonstrated in Figure 3.1, is based on the process of solving engineering problems and includes four main phases: (I) analysis, (II) development and implementation, (III) validation, and (IV) Conclusion.

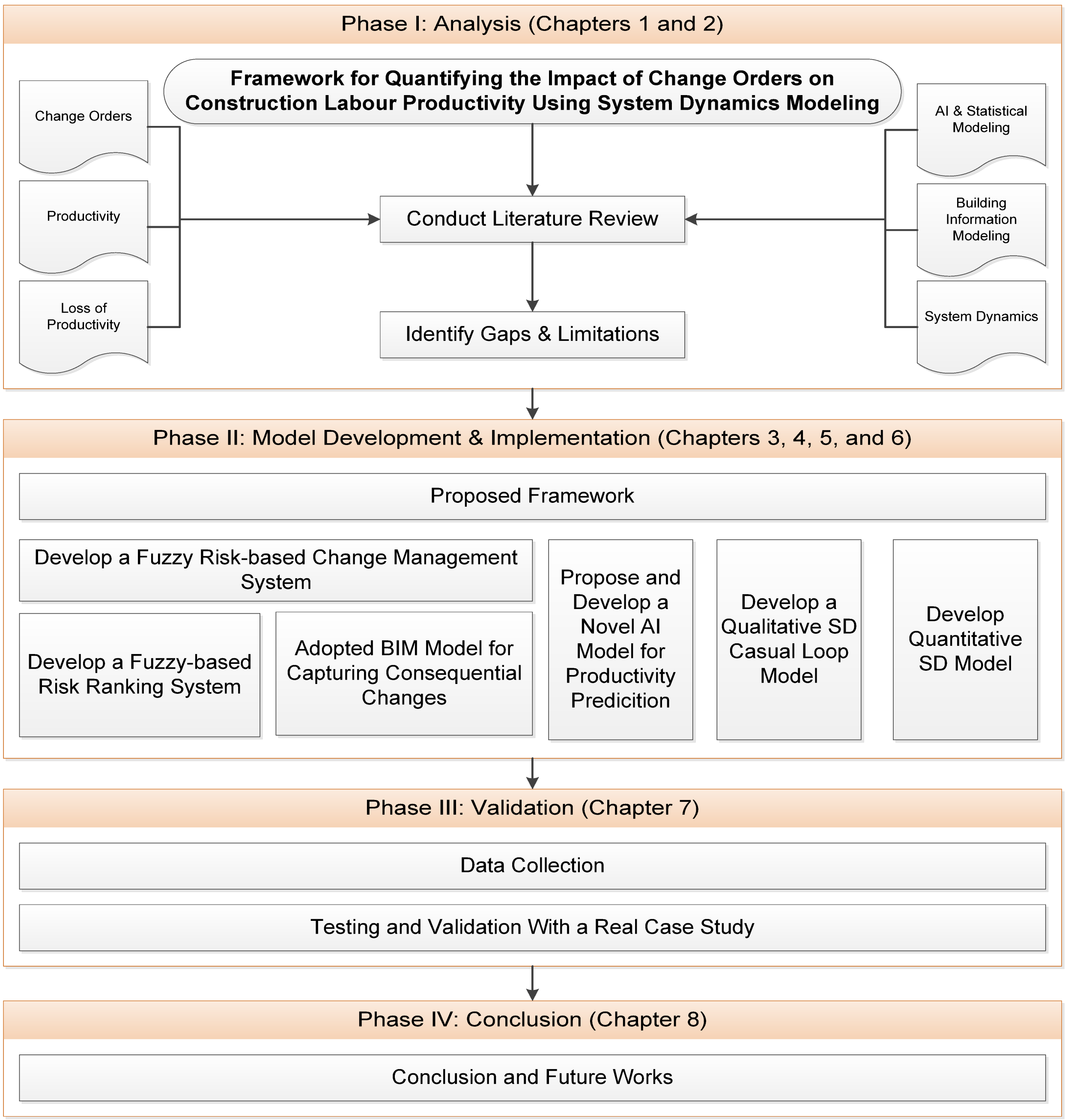


Figure 3-1. Research Methodology General Overview.

Phase I included a comprehensive review of existing studies on construction labor productivity, change orders, and loss of productivity found in the literature. This stage was the building block of this research and helped to frame the research problem statement and objectives. The results of the analysis phase highlighted the drawbacks of the current practice in the quantification of productivity loss due to change orders in the construction projects. These drawbacks led to a course of action, which was performed in the development phase. Phase II included a description of the four main components of the proposed framework. These were the development and implementation of FRCM including FRR and BIM, an AI model, and finally, Qualitative and Quantitative SD modeling. The validation phase (III) involved validating the developed models using a real-world case study adopted from the construction field to demonstrate its application. Finally, the conclusions, recommendations, limitations, and future improvements were described in the conclusion phase (IV).

3.2 Phase I - Analysis Phase

A broad literature review was performed in Chapter 2. It focused on a wide range of research in construction project changes and change orders, loss of productivity and its quantification, BIM, continuous simulations, Statistical Productivity Modeling, and AI techniques and their applications in construction management. The literature review concentrated first on the characteristics of changes in construction projects and their adverse effects on all the aspects of a project as well as the reaction of decisions makers to changes. BIM applications used in construction projects specifically in order to capture consequential changes that may arise from initial change(s) were investigated. The next part discussed construction labor productivity, identification of the influential elements/factors that cause loss of productivity, and the current techniques for quantifying the loss of productivity due to change orders. SD modeling as a continuous simulation method was investigated to calculate the loss of productivity. The model was discussed and analyzed from the perspective of both theory and application. Procedures for developing an SD model and its advantages and disadvantages were outlined. In order to achieve the research objectives and in order to avoid the limitations of SD modeling, mathematical complexity, and the tremendous number of equations, Statistical Productivity Modeling and AI techniques were reviewed and investigated to estimate BP. Finally, the shortcomings associated with current methods were described and presented in Chapter 2.

3.3 Phase II - Model Development and Implementation

This phase was based on the results of the previous phase. The development phase mainly involved the creation of different required components in terms of an integrated framework. The major components of the proposed integrated framework components have been developed and implemented are shown in Figure 3.1. The first step in this phase was to develop a prototype Fuzzy Risk-base Change Management (FRCM) which included two main modules: namely “FRR” and “BIM model”. The first module was capable of providing guidance, as well as a systematic approach for prioritizing changes during the course of a project. The second module was an adopted and modified BIM model to ensure that the proposed integrated framework will have the ability to capture any consequential changes that may arise from the imposed initial requested changes. The third component included developing a proposed AI technique so that the framework can portray the effects of influential environmental and operational factors on labor productivity estimation. The fourth component of the proposed framework included the development of a qualitative SD model representing the influential elements that create real project behavior. Developing a quantitative SD model that focuses on how policy-driven variables behave and interact with each other and how productivity will be impacted by those variables was the fifth component. The integrated frame in this research includes a holistic enhanced SD model for quantifying the loss of productivity due to change orders. All these components were then integrated in this phase. Each step is elaborated in more detail in the following Chapters 4, 5, and 6.

3.5 Phase III – Testing and Validation of the Framework

Phase III used a real-world case study from the construction domain. This implementation had three major components: data collection, applying the proposed integrated framework, and analyzing results. Data from a convoluted, real construction project was collected using a data collection process. This process included the collection of multiple forms of project data, including reference models and influential variables. This phase is where the proposed integrated framework and its application were tested and validated. The proposed framework is simulation-based and is almost exclusively a computer-based process. Accuracy in simulation-based systems relies mainly on the precision of the data used to build the simulation model, as well as on its simulation. Validation of the proposed integrated framework and its application as a two-step process are as follows: a) Validation and testing of FRCM, PSO-RBFNN, and the SD model. The SD model was tested, and SD robustness was assured. The validation process was based on Sterman’s guidelines (2000); and b) Comparing the results of the proposed framework against the actual project data.

3.6 Phase IV – Conclusion, Recommendations, and Future Work

The closing observations on the proposed framework are stated in this phase. A comprehensive discussion of the challenges found, and lessons learned are explained in this section. In addition, a summary of the discoveries and some potential topics for future research are outlined. Finally, this research ends by assessing the limitations of the proposed method and noting some of the most promising enhancements.

3.7 Summary

This chapter outlined the overall research methodology followed to achieve the research objective. The methodology included five phases as follows: 1) Literature review; 2) Development and Implementation; 3) Validation; and 4) Conclusion. The major components of each phase were described in a holistic view. A broad literature review of the current state of research was conducted as part of the analysis phase. The second phase was the development phase, which covered the major components of the proposed framework including FRCM (which consisted of FRR and BIM), an AI model, and Qualitative and Quantitative SD modeling. Testing and validation were conducted in the third phase using a real-world project from the construction industry, and the last phase encompasses presenting the findings and lessons learned from the research.

4. CHAPTER FOUR: FUZZY RISK-BASED CHANGE MANAGEMENT

4.1 General Overview

Changes in construction projects are often caused by vague and imprecise information at the early stages of the project. Potential changes taking place throughout the course of a project are one of the main causes of risk in construction projects. Risk has different meanings to different stakeholders; risk definition is contingent upon the perspective and experience of the people involved in the project. Consulting engineers see the risk from a technical viewpoint, while clients and contractors see the risk from an economic and financial perspective. The Business Dictionary defines risk as "The exposure to a company that arises from taking on a particular task. Project risk can be internal to the business, it can involve external events or it can stem from any other circumstances that can hamper the project's overall success and result in loss or embarrassment to the firm undertaking it" (Business Dictionary, 2016).

One of the most important risks in construction projects is the failure to meet the initial estimate of the project parameters. Project parameters are usually stated as targets established for cost, time, quality, performance, scope, and project purpose. Thus, the likelihood of failure to meet planned targets may increase if changes are not managed through a formalized change management process. If changes are poorly managed, they can become a major cause of costly disputes, which is a rigorous risk contributing to project failure. Many change management processes and models focus on identification and recommendation for handling changes which are not enough to manage changes effectively during the course of a project. In other words, currently available change management models mainly focus either on the change identification process, best practices for managing changes during a project, or the evaluation of change impacts on only a single project aspect. Building a robust construction change management model is a convoluted task because it requires a comprehensive solution that synchronizes all the inputs coming from the different parties concerned for managing changes. In this chapter, the FRCM model and its first two phases, FRR and BIM, are further elaborated. It is worth noting here that change and change order are two different concepts; when a change request is approved, it can be called a change order. Consequently, change or change request refers to a change that has been registered and requested but not yet approved for implementation, while a change order refers to a change request that has been approved for implementation. This chapter elucidates on the FRR that may have the potential to reduce and remove unnecessary changes to create a successful change management process. The objectives of this chapter include proposing an FRR for change management and proposing a framework for this purpose. Chapter 4 proposes a robust change management model to ensure that each change introduced in a project is appropriately defined, assessed, and accepted or rejected based on its risk ranking score prior to execution.

4.2 Fuzzy Risk-based Change Management Model

As Figure 4.1 demonstrates, the complex integration of various information necessary for the development of a sound change management model is a challenging task.

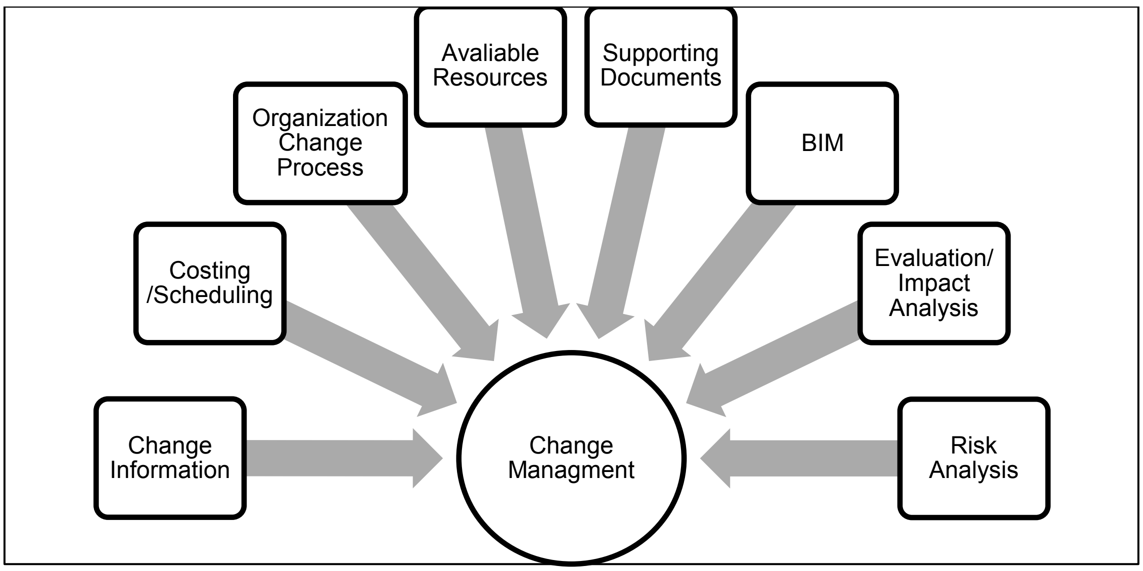


Figure 4-1. Information Required for a Holistic Change Management Model.

Changes in construction projects are inevitable. Usually, they are not well defined, and it takes considerable time and effort to gather all the changes information. A change management model can be defined as an essential tool for cooperating internal and external factors that influence proposed changes. Previous research on managing changes in construction projects can be classified into three major groups:

1. The first group covers processes, guidelines, and the best practices for managing changes (CII, 1994; Cox et al., 1999; Ibbs et. al., 2001);
2. The second group covers the effects of a change order on a certain project aspect. For example, Williams (2000) tried to show the impact of safety regulation changes on a project by using the System Dynamic (SD) modeling technique; and
3. The last group covers change management models. Pelton et al. (1993) developed a change document management system that integrates document approval and release procedures. Meanwhile, Hegazy et al. (1994) developed a model to facilitate design

coordination and management of design changes. The proposed model is capable of identifying the ripple effects of changes by considering dependencies among building elements. Charoenngam et al. (2003) proposed a web-based change order management system that supports documentation practices, communication, and synchronization between different team members in the change order workflow. Lastly, Motawa et al. (2007) developed a proactive change management tool composed of a fuzzy logic-based change prediction system and a system dynamics model of the Dynamic Planning and control Methodology (DPM), which is used to assess the undesirable impacts of changes on construction performance. Karimidorabati et al. (2016) developed a three tiers automated change management model for megaprojects.

A proper change management model should encourage positive changes which do not affect the project negatively and mitigate unfeasible and negative changes. It should also serve as a tool for managing changes by integrating various information throughout the course of a project. Thus, in order to develop an effective change management model that incorporates all of the above, the developed model has to take into consideration the following:

1. Identifying changes (changes can be caused due to the design changes, budget shift, error or omission, etc.);
2. Identifying change type (mandatory or elective);
3. Communicating changes with all appropriate project stakeholders as early as possible after the change has taken place;
4. Identifying and capturing consequential changes;
5. Estimating the cost and time required for changes and their ripple effects prior to execution;
6. Prioritizing and ranking the proposed elective changes using fuzzy-based risk ranking by the change originator and risk analyst;
7. Approving or rejecting proposed elective changes by consensus among management team and client in an effective and timely fashion;
8. Informing project team of any necessary actions;
9. Facilitating the final approval and handover process by sending the client notification of the performed changes; and
10. Recording lessons learned for assessing similar changes in the future.

This section describes the development of FRCM model, the techniques used at each stage, and the function of the prototype model. Assessing indirect change impacts on projects has become increasingly difficult; as projects grow in complexity in terms of project delivery systems and contract types, there is a high dependency on the professional judgment of the project team. The aim of the FRCM prototype model is to facilitate the change assessment process as well as provide accurate and comprehensive information to decision-makers. Sharing the lessons learned from previous projects among the project team results in informed decision-making and can improve the change assessment process. It is highly recommended that the knowledge gained from previous projects regarding changes be shared with the project team globally and through well-established communication channels rather than by banking on socially built communication channels. The developed model can help the project management team make better-informed decisions on any proposed changes by making the lessons learned information formalized and easily available. For example, using the developed model, the project team can check whether a similar change has occurred in other projects and how that change assessed previously. FRCM can retrieve historical data for this purpose. The workflow diagram in Figure 4.2 outlines the developed change management model process. FRCM model contains procedures, policies, documents, and templates for assessing and managing changes over the lifecycle of a project. FRCM model is a tool for change management but it should be noted that it is the obligation of the project management team to make sure that the proposed changes are managed in respect to the company's policies and procedures. Multiple changes to a project can increase the change management complexity; it is unrealistic to believe that change data can be conveyed effectively among project parties without some form of project management tool. The literature review findings in conjunction with the feedback of industry experts employed in several North American mega projects helped to identify the importance of having a workable construction project change management framework.

4.2.1 Change Identification and Registry

Since changes are an integral part of construction projects, the goal of all project parties, clients, designers, and contractors, is to reduce the number of changes affecting the project negatively. Consequently, change identification and management should begin before even the execution phase of a given project. Change identification is required for the implementation of an effective change management model. However, change identification is hard to automate, as it requires considerable effort to reach an intelligent proactive system. Thus, proactive change identification is out of the scope of this research. In the developed model, the originator of the change identifies the need for a change when there is a difference between the project current situation and the project's planned situation. Here, the need for a change for a given project is carried initiated out by the change originator based on symptoms, errors and several other project characteristics which may lead to project changes. The project's contract documents play a significant role in this step. The originator should know the contract requirements conditions in terms of scope, specifications, schedule, and budget so that any deviation can be captured and assessed in a timely fashion.

In this research, consequential change identification has been automated using a BIM-based change management model because of its strong visualization and parametric modeling capabilities. Utilizing BIM for the identification of consequential changes will be further explained in the next following sections. To keep track of changes, it is important that all changes are registered, along with any information essential for assessing and managing changes including but not limited to:

1) Impacted areas; 2) Concerned departments; 3) Due date for approval; 4) Due date for execution (planned and actual start and finish dates); 5) Change description; 6) Reason for Change; and 7) Change Type. Several classifications for Change Type and Reason for Change exist in the literature. For the purposes of this research, the CII (1994) classification of change was adopted and includes the following:

- Mandatory Changes: These changes are required to be implemented to meet the objectives and any regulatory, legal contractual, safety, and engineering requirements and standards. In other words, ignoring these changes will have a negative impact on the client's reputation and overall project; and
- Elective Changes: These changes can enhance the project but are not needed to meet project objectives. It is assumed that these changes may reduce project cost, schedule, or degree of complexity. It should be noted that a change at the primary phase of a project can be realized as an opportunity to improve the project; however, it is likely that these changes will diminish as the project progresses.

As previously mentioned, changes in construction projects may occur due to many reasons such as unforeseen site conditions, lack of fulfillment of client's need in project design, design errors, and imposed uncommon rigorous requirements by design engineer. The United States Pacific Command (USPACOM) uses a reason coding system for change administration and management facilitation (Stocks and Singh, 1999).

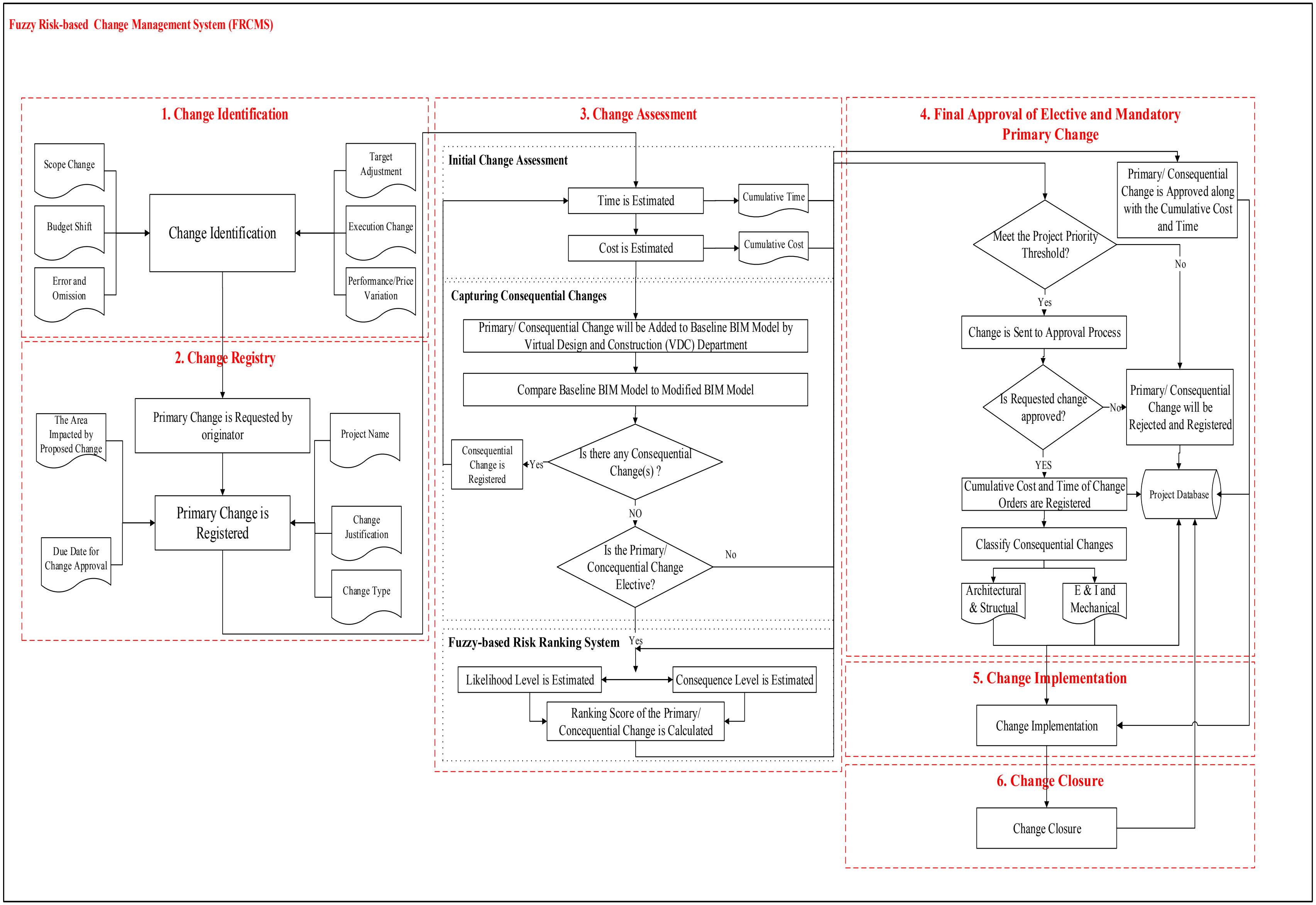


Figure 4-2. Proposed Change Management Model.

To help unify “Reason for Change,” the USPACOM coding system was adopted, modified, and built-in to the developed change management model. Table 4.1. Figure 4.3 illustrate the change identification and registration steps.

Table 4-1. Reasoning Coding System.

No.	Code	Description
1	CREQ	Clients Requested Changes
2	CRIT	Requested Changes due to criteria changes
3	DSER	Requested Changes due to design error
4	UNFO	Requested Changes due to unforeseen conditions
5	UNIL	Requested Unilateral changes where no agreement could be reached
6	VALE	Requested Changes due to value engineering
7	SCAL	Requested Changes due to scope alteration
8	TPAC	Requested Changes due to third party actions
9	DESC	Requested Changes due to deleted scope
10	PRVA	Requested Changes due to price variation

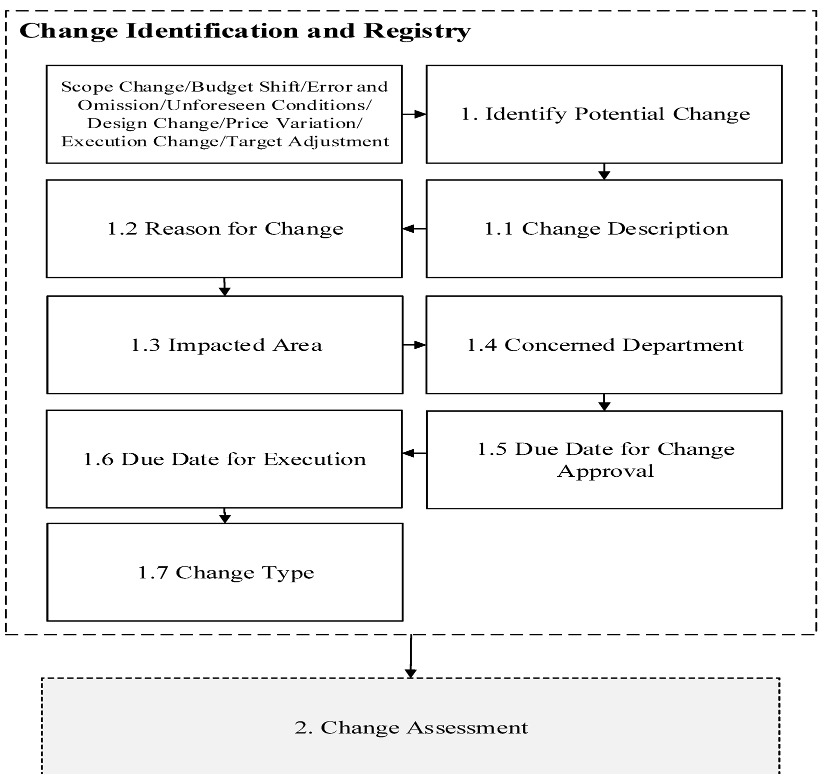


Figure 4-3. Change Identification and Registry.

4.2.2 Change Assessment

The main aim of the change assessment step is to decide whether a requested change should be accepted and implemented or rejected based on its type and risk ranking score. This step analyses potential change impacts on project time, cost, and organizational aspects. In this step, different options are analyzed to find the optimum one for decision-making process facilitation. Based on the results of this step, project decision-makers can decide whether or not to proceed with any of the possible changes or to carry out more investigations. The result of the assessment is a change request which summarizes the change and its associated cost and time impacts. Figure 4.4 shows the overall change assessment process.

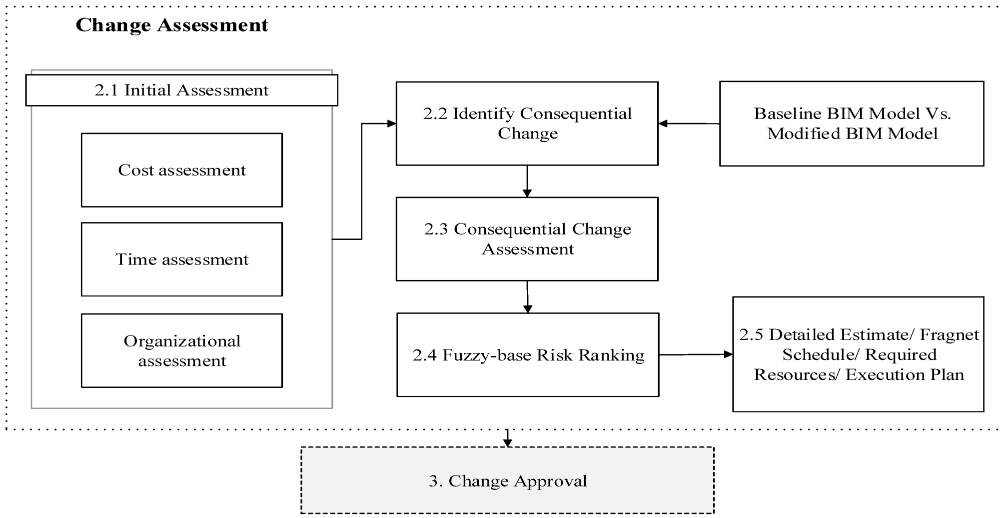


Figure 4-4. General Overview of the Change Assessment Process.

4.2.2.1 Initial Change Assessment

It is very important that all project parties ensure how contract clauses outline the change order procedures and processes. Both parties, owner and contractor, should be able to determine the cost of a potential change or review and validate the proposed price through a frontend estimating technique. Put differently, project parties should have the confidence that the proposed change delivery cost is fairly and more realistically calculated. Three methods are available for calculating change cost, namely unit price, lump sum, and time and material. Reviewing change time and the cost is highly contingent upon the client agreed method of calculation and includes the following:

- **Unit price method:** This includes the total estimate of the direct and indirect costs, overhead cost, profit, and contingency. After proposing and having the unit price approved by the client, the unit price for performing the proposed changes is then established in the contract. To evaluate the proposed change cost, the client should verify the material quantity installed by the contractor;
- **Lump sum method:** This method requires a detailed estimate prepared by both parties independently. The client's estimate will be used as the basis for validating the

contractor's proposed change submission. The detailed estimate should include material quantities, labor production rates, and pricing; *and*

- **T&M method:** T&M is based on the contractor's actual direct costs (labor, equipment, materials, etc.) for implementing a change including overhead and profit mark-ups. This method is riskier for the client and requires more rigid controls from the client side. Usually, a ceiling price is agreed upon by the client and the contractor and a potential change cannot go over the agreed-upon price.

It should be noted that, regardless of the agreed-upon pricing method for a change order, a detailed estimate must be prepared and accompany a contractor's submission to the client. In order to calculate the cost of implementing a requested change, various required costs including Direct Field Labor (DFL) Costs, Material Costs, Equipment Costs, and Third-Party Costs have to be taken into consideration. Time assessment of a requested change is as important as cost assessment since it is possible the project schedule will be impacted or delayed by the work included in executing a change order. The impact of a requested change can be absorbed by consuming the affected activities' total float. On the other hand, if a change is found to be on the critical path of the project, the agreed-upon completion date may slip. Likewise, when it comes to time assessment, it is important that the owner and contractor be able to perform time impact analysis for a project to identify the activities impacted by a proposed change and to verify if the project completion date has slipped or not. The duty to mitigate damages caused by change orders is the responsibility of both parties (contractor and client). Thus, the timely identification of potential project issues and delays helps both parties establish a recovery plan to mitigate some or all potential delays. The method(s) of performing schedule analysis, format, and submittal of requested changes, the approval process, as well as the ratified fragnet schedule incorporation into the project should be outlined in the project contract. Several techniques are available for quantifying the impact of change orders on project schedule such as "Window" Analysis, Collapsed As-Built, Impacted As-Planned, and Time Impact Analysis (TIA). Among the mentioned techniques, TIA can be considered as the most common and suitable technique for evaluating the time-related effect of changes on the project schedule and contract duration. To quantify the time extension entitlement, this technique requires that the contractor prepare a fragnet schedule and use the updated schedule in effect at the time a change was issued. The complete TIA procedure and requirements are comprehensively explained in AACE® International Recommended Practice No. 52R-06, 2017 (AACE, 2017). The developed change management model does facilitate TIA implantation by providing some essential information such as required man-hours, description of the change, impacted area, etc. The effect of requested changes on an organization, however, is out of the scope of this research and will be considered as the future development of this research.

4.2.2.2 Consequential Change Assessment

Identifying consequential changes prior to their occurrence may help the project management team to manage changes more efficiently and effectively in a timely fashion over a project lifecycle. Consequential changes are defined as any changes which may arise as the result of a new change request initiation by either party (owner or contractor). Identifying consequential changes is not an easy task; it is not unusual in change management models that consequential changes be overlooked while a new requested change is being initiated. Therefore, a holistic change identification process for any change management model cannot be based on traditional methods, paper-based printouts of 2D drawings, as this does not permit all the effects of a requested change to be discovered. As construction projects increase in complexity, so identifying consequential changes and clashes between different discipline-specific models is becomes an onerous convoluted process. BIM software, capable of demonstrating both the physical and essential properties of building elements as an object-oriented model tied to a dynamic database and parametric modeling capability, can rectify this problem by visualizing the impact of a requested change on other project components. Plenty of recent research has highlighted the advantages of BIM in design change management (Moayeri et al., 2015 and Pilehchian et al., 2015). The model adopted in this research uses BIM-based software developed by Moayeri (2017). The software is a computational platform that allows project parties to leverage BIM data for increased project insight, progressive project teamwork, and data-driven decision-making. It should be noted that using BIM-based modeling for consequential change identification is recommended for design changes only. Normally, design changes influence project cost and time and have the capability to increase the possibility of conflicts among project parties. In addition, any design change, regardless of whether initiated by the owner or A/E may have an impact on what appears to be the unchanged project scope. Thus, parties should consider that change in one part of the project might trigger a series of changes in other unchanged parts of the project, known as "consequential changes." Moayeri et al. (2015) classified design changes into four groups: adding, deducting and altering one or more components in the original design, as well as a combination of these categories. The process of using a BIM-based platform for consequential change identification is highlighted in the following diagram (Figure 4.5). The developed model by Moayeri has two main functions;

first, it finds the consequential change(s) of the design change on other project parts. Second, it quantifies the total impact of a change on project cost and time. The automated model is called "BIM-Change" and makes it possible to visualize consequential change(s). The first step in the "BIM-Change" software to develop a BIM model using the project's 2D drawings for different disciplines and project specifications documents. This can be carried out by the virtual design and construction (VDC) department. At this stage, the developed model should be saved as the baseline BIM model. Although the contractor is responsible for checking the drawings after being awarded the contract, it is not unusual in the construction industry for the drawings and specifications at bid time to be different from the IFC drawings. It is recommended that the baseline BIM model be prepared based on the bid documents to help identify any overlooked changes and variations. The second step is to develop a modified model based on the requested change. The change originator should disclose all essential information to the VDC department for the modified version of the BIM model. Then, both the models should be uploaded into the "BIM-Change" software for the highlighting and identification of impacted components and consequential changes. Finally, in the last step, to see the difference between the original and changed components, the user would analyze the generated report, which includes all the impacted components and information about the original components. It is very important to mention that the BIM model should be updated regularly based on the latest information at different stages of the project. This process is referred to as "Statusing" in this research. Statusing is a term used in scheduling practice which can be adopted for BIM modeling. BIM model Statusing is the process of updating a BIM model with requested changes and new sequences to reflect the actual situation during the lifecycle of a project. BIM model Statusing is a fundamental step to efficient planning and is a required step for an effective change tracking process. The benefits of updating the BIM model on a regular basis include: 1) Knowledge of whether components were modified, deducted, or new components were added; *and 2)* Continually tracking changes and their consequences on project components. After identifying consequential changes, the next step is to determine the time and cost assessment of the identified consequential changes using methods explained in Section 4.2.3.1. For the sake of loss of productivity quantification, the impact of change orders will be measured in absolute terms, meaning that a project's deductive and additive changes are treated the same regardless of their signs. For example, if an additive change costs X and a deductive change costs -X, the total amount of change considered for quantification will be 2X. This idea was adopted from Ibbs (2005) and the rationale behind this idea is that a deductive change may have the same impact on productivity, just as an additive change might.

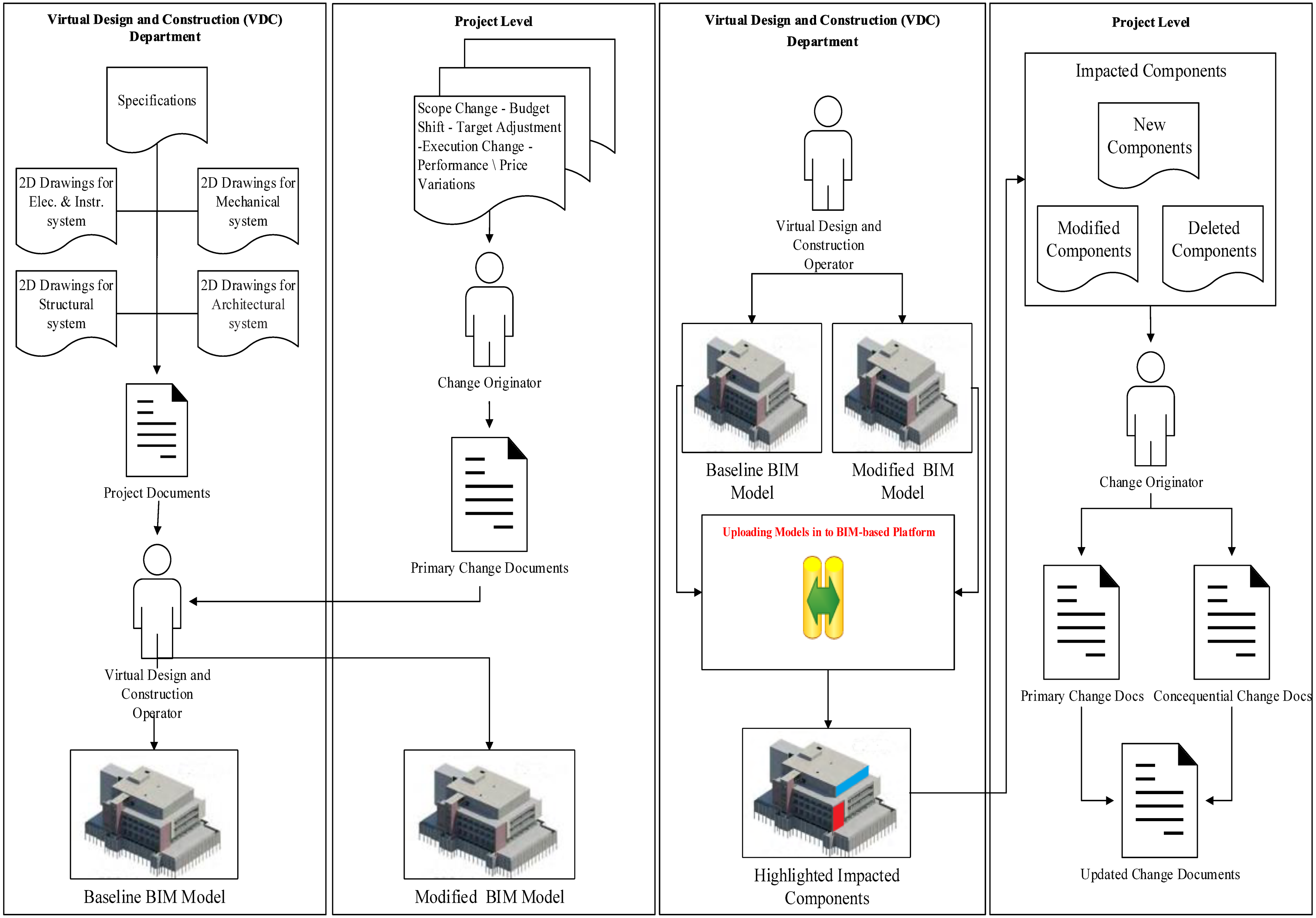


Figure 4-5. Capturing Consequential Changes Using BIM Models.

4.2.2.3 Fuzzy-based Risk Ranking Model

As mentioned previously, the considerable volume of qualitative information with questionable accuracy in projects makes it prone to many changes. Much of the information available for change management is based on individuals thinking in terms of conceptual patterns and mental images rather than quantities or numbers. A robust practice of gathering the information that encourages necessary changes and discourages unnecessary ones is required throughout the project process. There are several approaches to modeling uncertainty and variations of subjective variables including ANN, Rule-based system, and FIS. The first two methods are not applicable to this research for the following reasons (Motawa et. al, 2006):

- Any rule-based modeling requires change information in the form of precise rules. This is not realistic in the context of a construction project because a considerable amount of change information is ambiguous and not easy to quantify, making it technically close to impossible to assess; and
- The ANN modeling technique relies on the “black box” and has limited capability to clearly identify possible causal relationships. More specifically, ANN does not provide sufficient detail to justify the outcomes of the ANN model. In addition, building a robust ANN model requires greater knowledge regarding issues associated with ANN modeling, which may mask the outcome of the model such as overfitting of the training dataset.

Considering the abovementioned reasons, FIS was found the most suitable ranking approach for the developed change management model. A fuzzy-based model is an effective way of dealing with linguistic terms and vagueness associated with changes over a project timeline. Change impact assessment is a complex subject shrouded in ambiguity. This difficulty stems from the subjective judgment and inaccurate non-numerical definition of the probability and degree of impact on various aspects of the project caused by changes. This approach can resolve some drawbacks associated with traditional methods of risk ranking and have major advantages over strictly numerical methods. Firstly, it allows the impacts associated with the change to be evaluated directly using linguistic terms. Secondly, quantitative information, along with ambiguous, qualitative, or imprecise information, can be used in the assessment in a structured manner with more flexibility in combining the impact of change and likelihood of impact occurrence. Therefore, a fuzzy-based risk assessment was developed to rank the proposed elective changes based on change consequences/impacts and the probability of their occurrence. Figure 4.6 shows the overall view of the developed fuzzy-based risk ranking model and its five major steps.

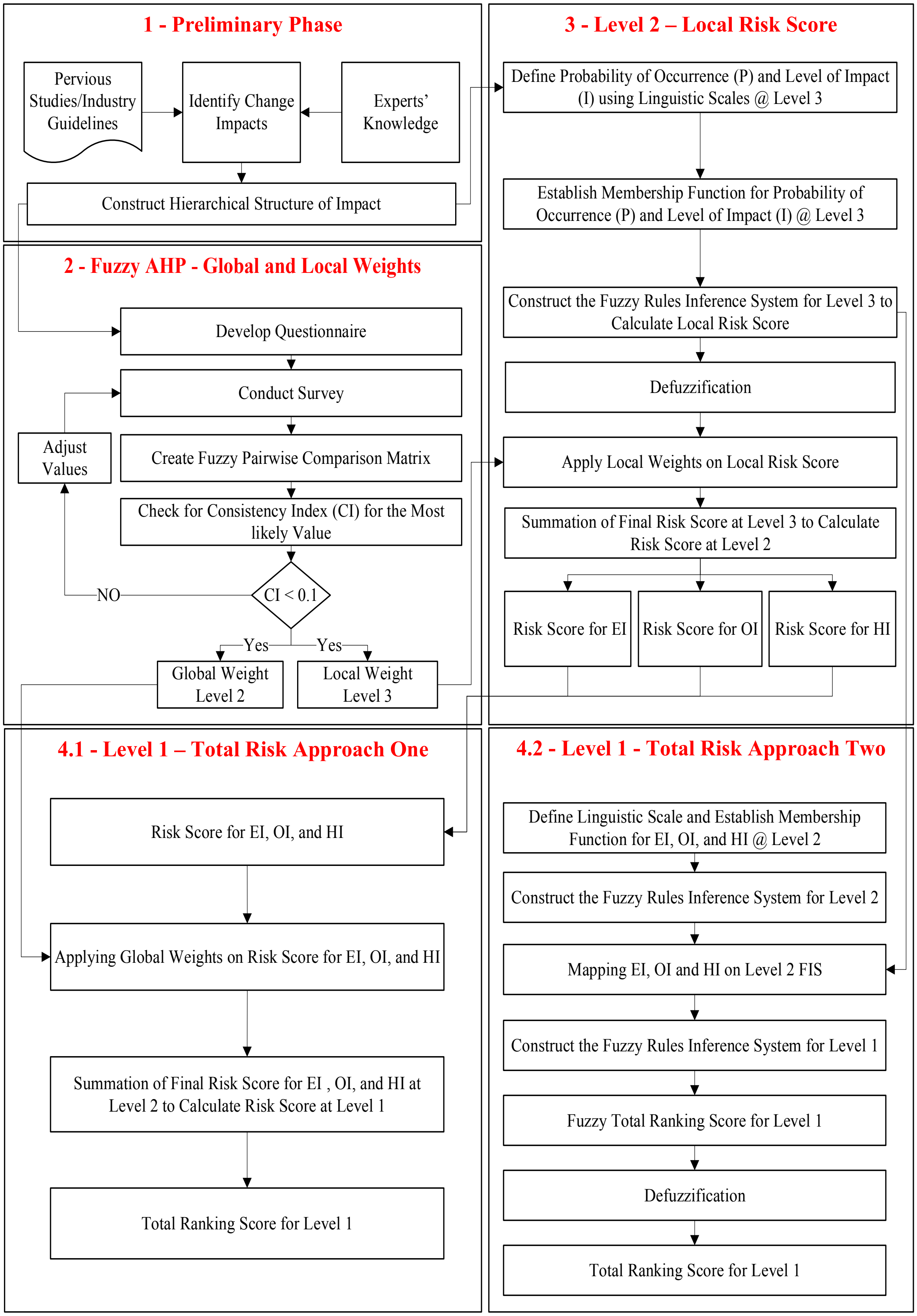


Figure 4-6: Fuzzy Risk-Based Ranking Model Overall View.

Step 1. Change Impacts Identification

This step helps to develop a hierarchical structure for the different possible impacts of the change under evaluation. Since various sources of impact affect construction projects in different ways, this research considers the source of impacts as a key factor in their classification. Therefore, a three-tiered impact structure was developed in this research, as shown in Figure 4.7.

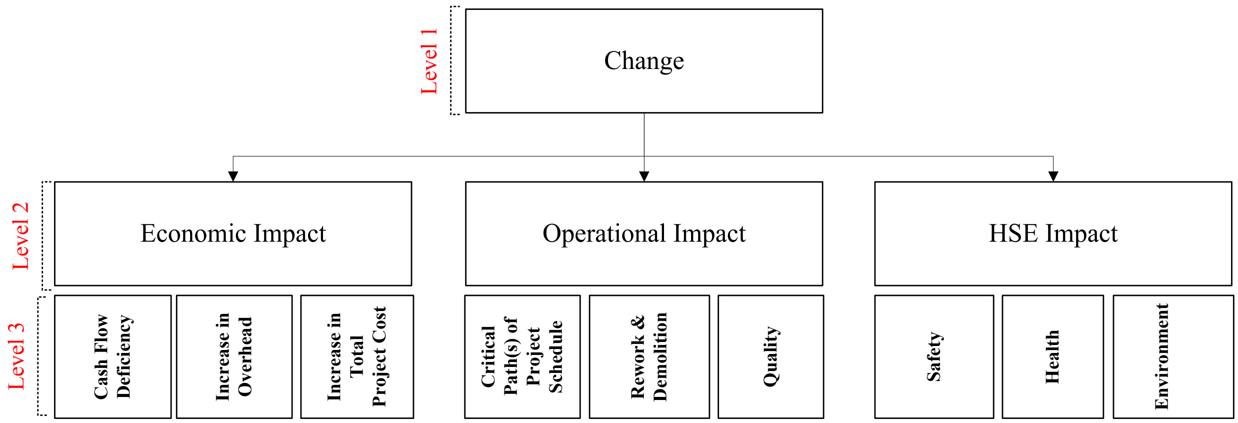


Figure 4-7: Hierarchical structure of Change Impacts.

The hierarchical structure was built in which the impacts at Level 2 were broken into simplest possible attributes. The reason behind this method is the fact that allocating occurrence likelihood and consequence level to the lower level of attributes are reasonably more straightforward than to the higher-level attributes. Change impacts include Financial, Operational and Health, Safety, and Environmental (HSE) impacts. Because the developed model is a reactive change management model, at the step in which a change occurred, the change impacts on the project were first identified, and then the occurrence likelihood of the identified change impacts was estimated. In the literature review, numerous studies highlighting the causes and impacts of change orders in construction projects were mentioned in Chapter 2. With this in mind and based on the study of the most important and frequently reported sources of impact, and construction industry experts' opinion, the following impact breakdown structure was developed (Figure 4.7). As shown in Figure 4.7, identified impacts can be classified into three major groups: Financial, Operational, and Health, Safety, and Environmental (HSE) impacts. All the above-mentioned factors have been reported as the impacts of changes, although there have been occasional variations in the applied terminologies and categorizations by different researchers. In each project, the identified impact can be customized considering various conditions, project specifications etc.

The first group considers impacts on financial sources. The impacts of this group happen as the result of additional costs associated with proposed changes and are as follows: 1) **Change in Cash Flow:** Cash flow is of great importance to construction parties as it prevents negative impacts such as liquidation and bankruptcy. However, securing cash flow can be difficult due to uncertainties, which are an integral part of any construction project. One of the major issues in large-scale construction projects is the uncertainty and ambiguity surrounding projected cash flows during the course of a project. According to Odeyinka and Lowe (2002), the main factors responsible for the deviation between projected and actual cash flow are changes to initial design as well as work variation. Zainudeen et al. (2010) found that the impact of design changes on cash flow plays a key role. Therefore, it is important that project parties secure additional interim finance than initially planned; 2) **Increase in the overhead:** Changes require a considerable amount of time and effort before they can be executed, as well as a solid processing procurer (O'Brien, 1998). The resources required to track, monitor, and execute changes in construction projects increase the overhead costs for all involved parties. Arain and Phen (2005) reported an increase in overhead costs as one of the most frequent effects of change orders; and 3) **Increase in total project cost:** The most common impact associated with change during the execution phase increases in project cost (CII, 1990a). Design changes can be considered a key factor in project cost overruns as identified by several researchers since design changes inevitably lead to deviation from the planned time and cost. Arain and Phen (2005) highlighted project cost increase as the most frequent effect of change orders. In the construction industry, it is common to expect a project cost increase due to multi-change orders during the course of a project. In other words, change orders affect total project cost and indirect and direct costs. Although a contingency fund plan over any potential unfavorable risks associated with changes in projects, it is not unexpected that several changes in a project may occur and exhaust the planned contingency. The second group of impacts associated with changes covers operational sources. These impacts, which may happen as the result of change orders, are as follows: 1) **Impact on Critical Path of Project Schedule:** The impact of change orders on project schedule can also be considered as one of the more frequents impacts. Major changes may affect the project completion day severely, and lead to costly delays. Ibbs (1997) found that completion schedule delays are generally caused by changes in construction projects. Assef and Alhejji (2006) conducted a survey in Saudi Arabia to determine the causes of delay and their importance to each of the parties involved in projects – the owner, consultant engineer, and the contractor. The results of their study show that the most common reason for delay identified by all three parties is a change order. Several factors should be taken into account to minimize the effect of change on project schedule such as comprehensive detailed design, mitigating employer-initiated changes, and complete site investigation and surrounding environment by project parties (Kumaraswamy et al., 1998); 2) **Rework and Demolition:** Changes may lead to rework and demolition of work in construction projects (Clough and Sears, 1994). Changes imposed by project parties during the construction phase, or even when the project is substantially complete, usually lead to costly rework and delays in project completion (CII, 1990). The cost of rework in construction can be as high as 10 to 15% of the contract value (Sun and Meng, 2009). Hanna (1999b) assumed the impact of a change order to increase from project inception to completion. This is because changes during the inception and design phase of a project do not need any rework or demolition. However, changes in design during the construction phase may cause reworks and demolitions on the construction site. Thus, the timing of changes is a very important contributing factor as mentioned by Moselhi et al. (2005) and Ibbs (2005). As a result, the impact of a variation in design during the construction phase is more rigorous than in the design phase; and 3) **Change in Quality.** Excessive changes can affect project quality because contractors want to reimburse losses by doing work in the cheapest or quickest way possible, overlooking rules or leaving a detail behind at the expense of a high standard (CII, 1995). Similarly, loss of productivity may also lead to poor quality (Arain and Phen, 2005). As stated by Sun and Meng (2009), a change order can indirectly cause quality degradation due to a higher workload and the need for resequencing of work. A higher workload may trigger different managerial policies like working overtime or adding more shifts to bring the project back on track. The key impacts of these kinds of policies on labor are ethical issue and fatigue which results in poor quality. The third group of impacts covers the HSE sources and includes: 1) **Safety:** Changes during the construction phase may lead to employing new methods, additional direct field labor, varied materials, and additional equipment. Thus, additional safety measures are required during the construction phase. Additional resources can lead to a more congested area at the construction site and possibly cause safety incidents; 2) **Health:** Any changes to the initial plan should be studied carefully to avoid negative impacts on human existence. For example, if a new change requires performing different Non-Destructive Tests (NDTs) or X-Ray inspection for field welding instead of Magnetic Particle Inspection (MPI), this should be taken into account prior to executing the proposed change; and 3) **Environmental:** The construction industry is one of the major global contributors to natural resource pollution both in physical and biological ways. Sustainability is a key concept in developing any new construction projects. Construction projects contribute to environmental degradation by contributing to the loss of soil and agricultural land, forests and wild lands, and air pollution. Although construction projects are crucial to all aspects of development, these projects should be designed and developed in a way that mitigates environmental degradation. By the same token, any new major changes initiated during the project lifecycle should be assessed with respect to environmental sustainability.

Step 2. Weighing Scheme Using Fuzzy Analytical Hierarchy Process (F-AHP)

A weighing scheme is essential for quantifying impact factor contributions in sub-criteria (Level 3), towards the criteria (Level 2), and the main goal (Level 1). For example, a change can have a schedule impact and contribute to an increase in overhead cost but the contribution of these factors to overall risk ranking value would not be equal, thus a weighing scheme is required. The F-AHP technique was utilized in this study to quantify the degree of importance of change impacts at a different level of the developed hierarchy (Figure 4.7). AHP first introduced by Saaty and Wind (1980), was applied to integrate expert feedback regarding the importance of various change impacts on the project. AHP can break apart a complex problem, down from higher hierarchy levels to lower ones, making it much simpler. Moreover, since the expert evaluation of change impacts on a project includes uncertainty and vagueness, the fuzzy set theory developed by Zadeh (1965) was applied. Therefore, the F-AHP method, which uses fuzzy numbers instead of real numbers to calculate the global and local weights of criteria and sub-criteria of each change impact, was selected to facilitate experts' judgments in a structured way (Ayhan, 2013; Lee, 2016). In this research, a survey was conducted to calculate the degree of importance (global and local weight) for each selected factor by experts. The questionnaire was distributed on March 15th, 2016 and all the responses were collected in a month. The questionnaire was designed on the Qualtrics data collection platform. More than 100 questionnaires were sent out and 42 were collected from various industry experts involved in different mega projects in branches such as, Oil and Gas, Hydropower Dam, Mining, etc. After the initial analysis, four questionnaires were discarded due to incomplete information. Thus, 38 questionnaires were used to calculate the degree of importance of various change impacts on a project. Years of experience and occupations of the experts are summarized in Figures 4.8 and 4.9. After gathering general information regarding the experts such as their job title and years of experience, industry experts were then asked to conduct pairwise comparisons between main criteria and sub-criteria under each main criterion to establish the relative importance of these factors in affecting project objectives. More specifically, industry experts were asked to compare the importance of each change impact against other change impacts in the same level with respect to its higher level by using linguistic variables, as shown in Table 4.2 (Lee, 2016).

Table 4-2. Linguistic Variables Fuzzy Fundamental Scale (Lee, 2016).

Linguistic Term	Fuzzy Number	Triangular Fuzzy Scale	Reciprocal Fuzzy Scale
Equally important	1	(1,1,1)	(1,1,1)
Intermediate value	2	(1,2,3)	(1/3,1/2,1)
Moderately important	3	(2,3,4)	(1/4,1/3,1/2)
Intermediate value	4	(3,4,5)	(1/5,1/4,1/3)
Strongly Important	5	(4,5,6)	(1/6,1/5,1/4)
Intermediate value	6	(5,6,7)	(1/7,1/6,1/5)
Very strongly important	7	(6,7,8)	(1/8,1/7,1/6)
Intermediate value	8	(7,8,9)	(1/9,1/8,1/7)
Absolutely Important	9	(8,9,10)	(1/10,1/9,1/8)

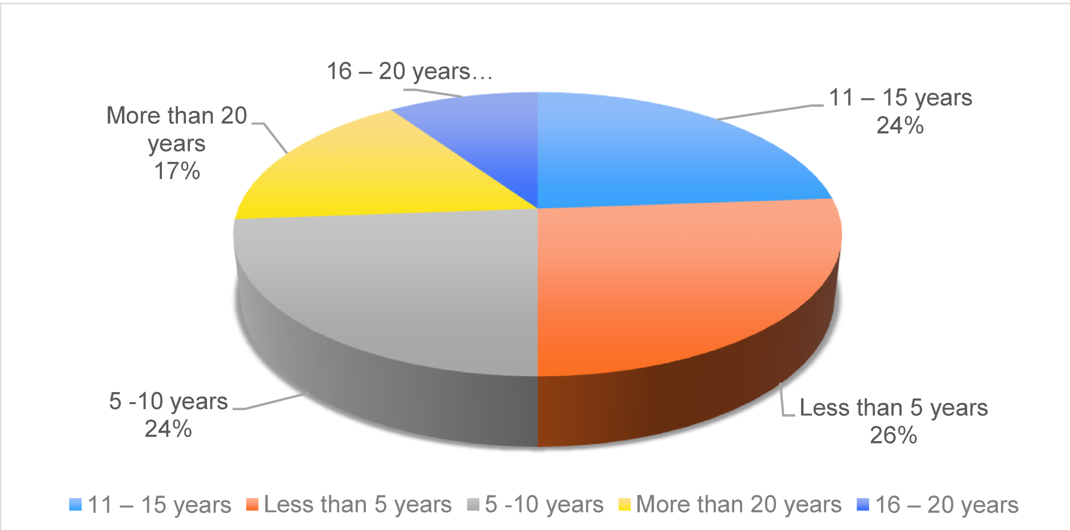


Figure 4-8. Participants' Years of Experience.

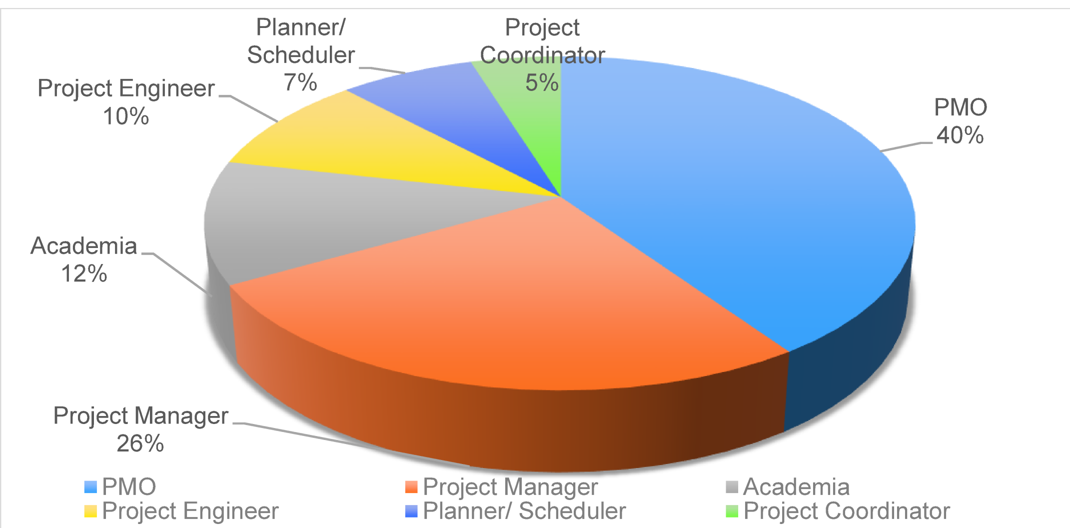


Figure 4-9. Participants' Occupation Type.

After the data gathering portion, F-AHP steps, as presented by Ayhan (2013), were followed. Industry expert replies were fuzzified by triangular numbers as shown in Table 4.3 and averaged using Equation 4.1:

$$d_{ij} = \frac{\sum_{k=1}^{K} dij^{k}}{K} \qquad \text{Equation 4.1}$$

Where $d_{ij}{}^{k}$ indicates the kth decision maker's preference of ith criterion over jth criterion and K indicates the number of experts. The average of the collected responses for the questionnaire is summarized in Table 4.3.

Table 4-3. Pairwise Comparison Matrix for Financial, Operational, and HSE Factors.

Main Criteria	Financial Impacts	Operational Impacts	HSE Impacts
Financial Impacts	(1, 1, 1)	(0.34, 0.45, 0.56)	(0.43, 0.53, 0.64)
Operational Impacts	(0.32, 0.43, 0.54)	(1, 1, 1)	(0.33, 0.44, 0.55)
HSE Impacts	(0.24, 0.34, 0.45)	(0.33, 0.44, 0.55)	(1, 1, 1)
Sub-criteria 1	Cash Flow Deficiency	Increase in Overhead	Project Cost
Cash Flow Deficiency	(1, 1, 1)	(0.31, 0.42, 0.53)	(0.31, 0.41, 0.52)
Increase in Overhead	(0.35, 0.46, 0.57)	(1, 1, 1)	(0.29, 0.39, 0.50)
Project Cost	(0.35, 0.46, 0.57)	(0.38, 0.48, 0.60)	(1, 1, 1)
Sub-criteria 2	Project Schedule	Rework and Demolition	Quality
Project Schedule	(1, 1, 1)	(0.35, 0.46, 0.57)	(0.39, 0.49, 0.61)
Rework and Demolition	(0.31, 0.42, 0.53)	(1, 1, 1)	(0.29, 0.39, 0.50)
Quality	(0.27, 0.38, 0.49)	(0.38, 0.49, 0.60)	(1, 1, 1)
Sub-criteria 3	Safety	Health	Environment
Safety	(1, 1, 1)	(0.34, 0.44, 0.55)	(0.42, 0.53, 0.64)
Health	(0.34, 0.43, 0.55)	(1, 1, 1)	(0.42, 0.52, 0.63)
Environment	(0.24, 0.35, 0.46)	(0.25, 0.36, 0.47)	(1, 1, 1)

In order to calculate the final relative fuzzy weights of each criterion, the following steps were followed:

Step 1: The geometric mean of fuzzy comparison values of each criterion was calculated using Equation 4.2:

$$r_i = \left(\prod_{j=1}^{n} d_{ij} \right)^{1/n}, i = 1, 2, \ldots, n \qquad \text{Equation 4.2}$$

Where, d_{ij} indicates the ith row and jth column of average comparison matrix for criteria and n shows the number of columns.

Step 2: The fuzzy weights of each criterion were then be calculated. First, the vector summation of each r_i was found, then the (-1) power of the summation vector, and the fuzzy triangular number replaced to make it in ascending order. Finally, each r_i was multiplied by this reverse vector. All the steps mentioned are shown in Equation 4.3:

$$w_i = r_i \otimes (r_1 \oplus r_2 \oplus ... \oplus r_n)^{-1} = (lw_i, mw_i, uw_i) \qquad \text{Equation 4.3}$$

Step 3: In this step, since w_i is still fuzzy triangular numbers, the center of the area as a de-fuzzification method needed to be applied, as represented by the following equation:

$$M_i = \frac{lw_i + mw_i + uw_i}{3} \qquad \text{Equation 4.4}$$

Step 4: Considering that M_i is a non-fuzzy number, it needed to be normalized as expressed by Equation 4.5:

$$N_i = \frac{M_i}{\sum_{i=1}^{n} M_i} \qquad \text{Equation 4.5}$$

All the above steps should be performed to find the normalized weights of both the main criteria and sub-criteria, namely as global and local weights. By multiplying each attribute weight with the related main criteria, the degree of importance for each attribute was calculated. Table 4.4 shows the Global Weights, Local Weights, and Degree of Importance obtained. The table reveals that Financial Impacts have the highest effect in change order ranking. Operational and HSE impacts were ranked as the second and third key factors, respectively. It is very important that the consistency in the pairwise comparisons be ensured. The developed comparisons matrices are vulnerable to inconsistencies and mistakes in expert preference replies, thus, two indices, Consistency Index (CI) and Consistency Ratio (CR), need to be calculated in order to ensure consistency based on the developed questionnaire. First, the maximum eigenvalue (λ_{max}) should be calculated as follows:

1) To calculate matrix J, each triangular fuzzy number should be replaced by a geometric average of it components in the comparison matrix; 2) The obtained comparison matrix from the previous step should be normalized; 3) Aggregated weight (AW) should be calculated for each alternative; 4) Weighted sum matrix (WSM) is calculated by multiplying AW to Matrix J; 5) Step 4 should be divided by AW to calculate λ_{max} for each alternative; *and 6)* The overall λ_{max} is calculated by getting the λ_{max} average for each alternative.

Table 4-4. Global and Local Weights for All Parameters.

Main Criteria	Global Weight	Sub-Criteria	Local Weight	Degree of Importance
Financial	**35.11%**	Cash Flow Deficiency	32.56%	11.44%
		Increase in Overhead	32.85%	11.53%
		Project Cost	34.56%	12.13%
Operational	**33.17%**	Project Schedule	34.78%	11.54%
		Rework and Demolition	32.10%	10.65%
		Quality	33.12%	10.99%
HSE	**31.72%**	Safety	34.92%	11.08%
		Health	34.77%	11.03%
		Environment	30.31%	9.61%

After calculating the overall $\lambda_{max,}$ the CI was calculated from the following equation (Equation 4.6), showing the consistency degree of deviation:

$$CI = \frac{\lambda \max - n}{n-1} \quad ; \qquad \text{Equation 4.6}$$

Where, λmax=maximum eigenvalue and n=dimension of the pairwise matrix. The second index, CR, is defined as the ratio between CI and RI for random comparison (Equation 4.7) and it is shown in Table 4.5 (Saaty and Kearns, 2014):

$$CR = \frac{CI}{RI} \qquad \text{Equation 4.7}$$

Table 4-5. Average random consistency (RI).

Size of matrix	1	2	3	4	5	6	7	8	9	10
Random consistency	0	0	0.58	0.9	1.12	1.24	1.32	1.41	1.45	1.49

CI and CR were summarized for all pairwise comparison matrices and the results can be seen in Table 4.6.

Table 4-6. Consistency in Pairwise Matrices.

Pairwise Comparison Matrix	**CI**	**CR**
Q1. Main Criteria	0.004	0.008
Q2. Financial Impact	0.002	0.004
Q3. Operational Impact	0.047	0.091
Q4. HSE Impact	0.003	0.006

After defining each criterion and sub-criteria weight, to generate a single risk score for each change impact at the lowest level of hierarchal structure (Level 3), the next step was to integrate the proposed change impact and its occurrence probability.

Step 3. Fuzzification of Risk

It is very clear that risk assessment is highly subjective and the process shaped by many factors such as management's understanding of the project, desire to mitigate the negative impact of any imposed changes on the project, lessons learned from past experience, and the risk tolerance culture of the organization. This research proposes an FRR model for decision-making facilitation regarding elective changes based on identified change impacts as shown in Figure 4.6. Many of these impacts are not easy to quantify or define due to vagueness and uncertainty associated with changes, as mentioned in detail in the previous sections. In addition, it is very common that in the complex construction projects, change impacts are described in linguistic terms. Therefore, to achieve a reliable and precise change risk assessment, it is important to have a common language defining change impacts and their occurrence likelihood in a project. Fuzzy set theory was used in this research to overcome the above-mentioned issues because it is able to effectively handle the vagueness and uncertainty associated with changes in construction projects. Prior to the identification of each change impact's level of consequences and occurrence likelihood, several meetings were held with a senior risk analyst at one of the largest Engineering, Procurement, and Construction (EPC) and EPC Management (EPCM) firms in Canada. To further develop the occurrence likelihood and level of impact consequence definitions, meetings were also held with an independent risk consultant. The feedback received from both was taken into consideration for the development of the consequences and likelihood matrix based on linguistic terms. The risk matrix model is one of the simplest risk assessment models for ranking proposed elective changes according to their occurrence likelihood and consequence level of impacts. Table 4.7 presents five linguistic terms and their probability and consequence definitions.

Table 4-7. Customizable Terms for Quantifying Impact Occurrence Likelihood.

Likelihood	Likelihood Description	Probability
VH	The change impact is expected to occur with absolute certainty	> 65%
H	The change impact is expected to very likely occur	35% - 65%
M	The change impact is expected to likely occur	10% - 35%
L	The change impact is expected to unlikely occur	0.1% - 15%
VL	The change impact is not expected to occur	< 0.1%

Any organization can adopt and modify these terms, which will help in establishing similar understandings for expressing the occurrence probability of change impact in an organization. Quantifying the potential consequence level of a change impact is an integral part of any risk evaluation model. Proposing a new change, quantifying all potential consequences is very difficult. While the consequence of change is expressed in terms of three major categories (Figure 4.6), the consequence level of each change impact can be expressed by linguistic terms as shown in Table 4.8. The values in Table 4.8 have been tailored to this research based on several meetings with project control professionals and a risk analyst working for mega projects in Canada. However, due to the dynamic nature of construction projects, the values shown in Table 4.8 should be modified according to project objectives and type. Table 4.9 shows the risk score magnitude for each impact at Level 3 by relating the consequence level with the occurrence likelihood.

Table 4-8. Customizable Terms of Consequence Level Quantification.

		Economic Impact			Operational Impact			HSE Impacts		
		Change in Cash flow	Increase in Overhead	Project Cost	Project Schedule	Rework and Demolition	Quality	Safety	Health	Environment
Very Low	VL	Change in Cash flow< 0.50%	Increase in Overhead < 0.50 %	Impacts on Project Costs < 0.50 %	Impacts on Schedule on < 1.50 %	Rework and Demolition< 0.50%	No Quality Degradation	A Near Miss, First Aid Injury or One or More Medical Treament	No or Little Concerns on Health	No Imapct on Sourding Enviorment
Low	L	Change in Cash flow0.51% - 5.00%	Increase in Overhead 0.51% - 5.00%	Impacts on Project Costs 0.51% - 5.00%	Impacts on Schedule on 1.51% - 10.00%	Rework and Demolition 0.51% - 5.00%	Limited Quality Degradation	One or More Lost of Time Injuries (LTI)	Slightly Concerns on Health	Low Imapct on Sourding Enviorment
Medium	M	Change in Cash flow5.01% - 10.00%	Increase in Overhead 5.01% - 10.00%	Impacts on Project Costs 5.01% - 10.00%	Impacts on Schedule on 10.01% - 20.00%	Rework and Demolition 5.01% - 10.00%	Noticeable Quality Degradation Required Management Approval	One or MoreSignificant Lost of Time Injuries (LTI)	Concerns on Health	Meduim Impact Within The Project Boundary
High	H	Change in Cashflow10.01 % - 15.00 %	Increase in Overhead 10.01% - 15.00%	Impacts on Project Costs 10.01% - 15.00%	Impacts on Schedule on 20.01% - 30.00%	Rework and Demolition 10.01% - 15.00 %	Noticeable Quality Degradation Unacceptable to Management	One or More Fatalities or Sever Damages	Harmful can casue Irreversible Health Issue	Meduim Impact Within Outside the Project Boundary
Very High	VH	Change in Cash flow> 15.00%	Increase in Overhead > 15.00%	Impacts on Project Costs > 15.00%	Impacts on Schedule on > 30.00%	Rework and Demolition > 15.00%	Project End Product is Effectively Useless	Significant Number of Fatalities and	Exterme Harmful can cause Serious Disabling illness	Major Impact Event

Table 4-9. Risk Matrix Rules to Determine Risk Score Magnitude.

		Likelihood				
		VL	L	M	H	VH
Consequence	VL	VL	VL	L	L	M
	L	VL	L	L	M	M
	M	L	L	M	H	H
	H	L	M	H	H	VH
	VH	M	M	H	VH	VH

After defining the occurrence likelihood and consequence level terms, this research utilized the basic concept of fuzzy set theory and showed how it can be used to prove the heuristic knowledge of the project management team. As mentioned earlier, assigning an occurrence likelihood and impact degree to the lowest hierarchy level is easier and more reliable than at higher levels (Figure 4.10). It should be noted that obtaining information for FIS could be accomplished with human experts or experimental data using different methods as classified by Jin (2012): 1) Indirect knowledge acquisition; 2) Direct knowledge acquisition; and 3) Automatic acquisition. Minimizing the total number of rules and their corresponding computation requirements is one of the most important issues in developing a FIS where the knowledge-based rules are obtained from experts. Since the number of the rules and the complexity of FIS will increase exponentially with a number of variables involved in the model, a hierarchical FIS was proposed in this research to minimize this problem. The overall FIS was divided into a number of low-dimensional FIS. By utilizing this approach, the number of rules was greatly reduced (Lee et al, 2003). Several approaches exist to dealing with a hierarchical FIS structure. The approach adopted in this research was to use the output of the last layer as crisp value as the input of the next layer in the hierarchical FIS. The advantage of this approach is the fact that it will reduce the uncertainty of the new result by reducing the number of fired rules in the new layer but at the expense of losing uncertainty information. A FIS was developed for applying rule-based knowledge for mapping likelihood and consequence into a risk score. The rules are in the form of IF-THEN rules. The fuzzy risk matrix structure can be represented in the form of fuzzy rules as follows: If the likelihood is l_a AND level of consequence is c_b THEN risk is r_c, where l_a, c_b, and r_c are fuzzy set for likelihood, consequence, and risk outlined on the universe of discourse. Fuzzy rules were developed based on a combination of five occurrence likelihood categories and five consequence level categories according to the developed risk matrix (Table 4.9). Thus, 25 rules were generated representing risk score magnitude categories.

To help produce the number of rules, as previously mentioned, several interviews were held with a senior risk analyst and consultant. There are several fuzzy membership functions (MFs) out there for representing linguistic terms in the form of fuzzy numbers such as triangular or trapezoidal fuzzy numbers. The developed FIS uses five triangular MF (TMF) for sub-criteria consequence and likelihood over the range of 0-10. During this stage, fuzzy MF for different sub-criteria was defined by the direct method with multiple experts approach (Klir and Yuan, 1995). The TMF was good enough to characterize most of the sub-criteria precisely. The MF was used to determine the degree of membership of fuzzy-based risk score to different sets expressed by linguistic terms as follows: Very Low (VL), Low (L), Medium (M), High (H), and Very High (VH). A simple FIS was developed for aggregating consequences and likelihood impact using the Fuzzy Logic Designer under MATLAB 2017a.

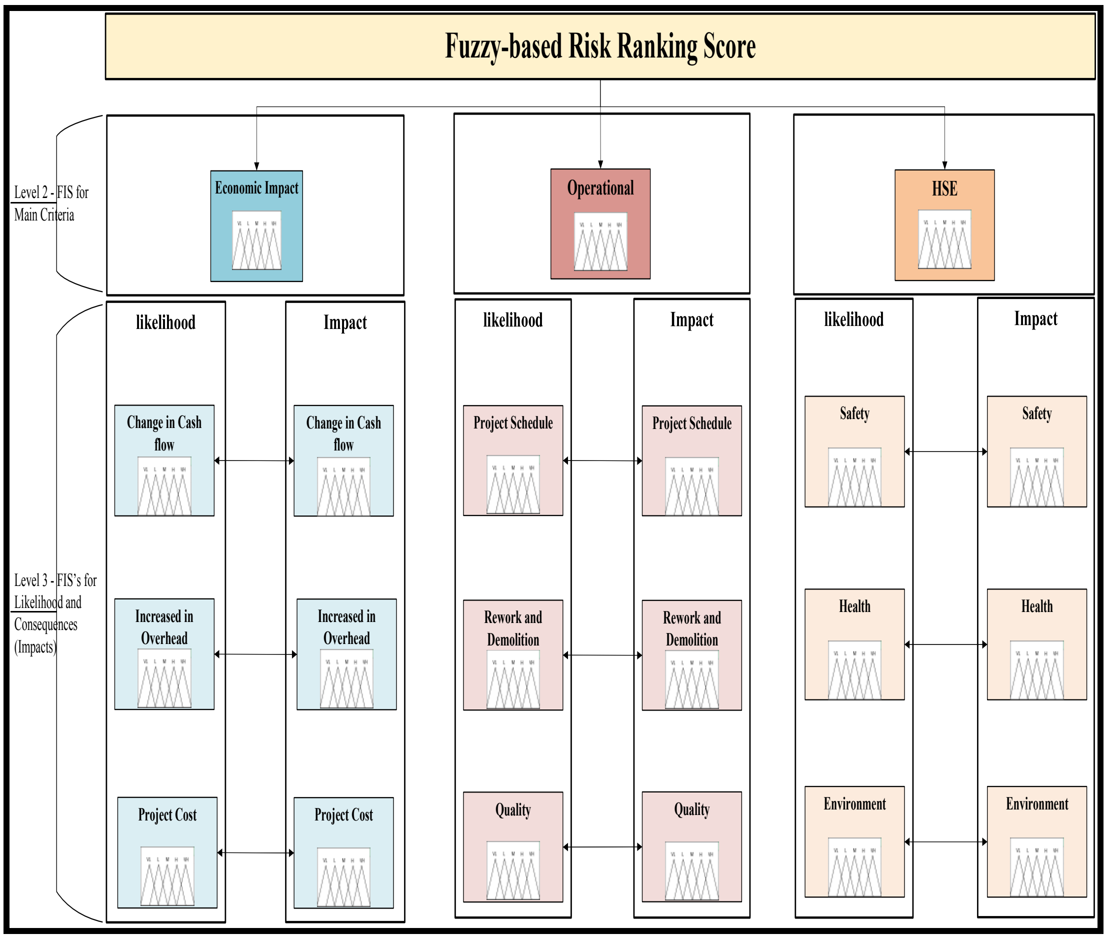


Figure 4-10. Fuzzy Inference Systems General Overview.

The developed FIS rules were established over several sessions with the risk expert. The rules represent expert knowledge and map the inputs to the output of the developed system. The Mamdani fuzzy rules system was applied to the developed FIS model. Mamdani has some advantages over Sugeno such as Straightforward formalization and interpretability, Acceptable results with comparative simple structure; and Frequently utilization for decision support application due to intuitive and interpretable rule-based nature., summarized as follows (Hamam and Georgana, 2008). The MFs for each variable along with the fuzzy IF-THEN rules were used to build the FIS. A conservative method for consequence and likelihood aggregation was used, namely as “Max” operator. “Min” was selected for implication and the centroid method selected for the defuzzification process. Centroid defuzzication is the most frequently used method. The only drawback of this method is that it is computationally challenging for complex membership functions. Figure 4.11 shows the local risk score surface that is the visual rendering of the relationship between the inputs and output of the developed FIS. Here, the surface presents the different local ranking score areas depending on input parameters. As shown, a high-ranking score is assigned when a change consequence level is high, while increasing the impact occurrence probability and a low consequence level does not result in a high-ranking score.

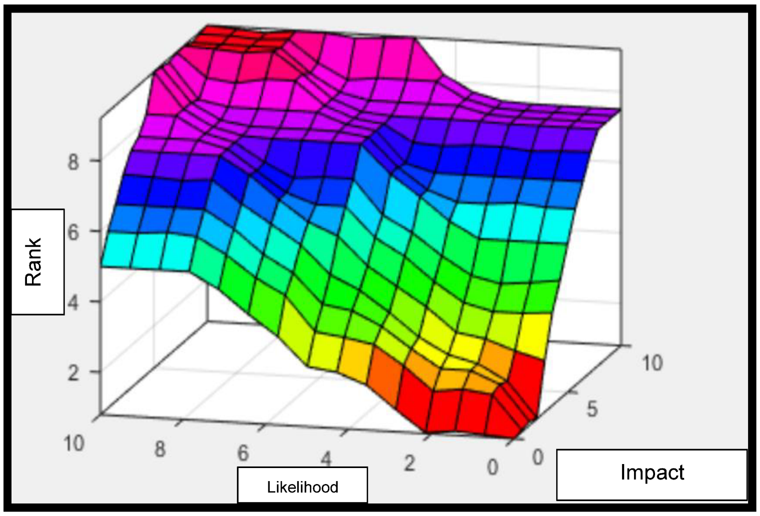


Figure 4-11. Local Risk Score Surface Visual Rendering

Step 4. Aggregate local risk scores for calculating the change risk score

Once the fuzzy local risk score and local weights for each change impact at Level 3 were quantified, the total ranking score for the proposed elective change was determined by employing one of the approaches explained further in the following sections.

First Approach

The first approach is very straightforward. The risk score for each change impact at Level 2 was calculated by grouping all sub-impacts under the same main impact. For example, X_{11}^{2} is determined by the following equation:

$$X_{11}^{2} = \sum_{i=1}^{3} w_{i1}^{3} * X_{i1}^{3} \qquad (i = 1,2, and 3) \qquad \text{Equation 4.8}$$

Where, X_{i1}^{3} is the risk score for a Level 3 change impact (such as cash flow deficiency) obtained from the developed FIS, w_{i1}^{3} is the local weight for the same change impact obtained from FAHP, X_{11}^{2} is the risk score for Level 2 change impact (such as financial impact), and i shows the number of sub-impacts at Level 3 under the main impact at Level 2. In the same way, the risk score for other impacts at Level 2 ($X_{21}^{2} and\, X_{31}^{2}$) is determined. The final aggregative risk score for Level 1 can be quantified using the following equation:

$$X_1^1 = \sum_{i=1}^{3} w_{i1}^2 * X_{i1}^2 \qquad (i = 1,2, and 3); \qquad \text{Equation 4.9}$$

where X_{i1}^2 is the risk score for each Level 2 main impact obtained from Equation 4.8, w_{i1}^2 is the global weight for impacts at Level 2 obtained from FAHP, X_1^1 is the total risk score for the proposed elective change, and i shows the number of Level 2 main impacts identified under a proposed elective change at Level 1.

Second Approach

Similar to the first approach and according to Figure 4.6, at this stage, the risk scores at Level 3 sub-impacts obtained from FIS were available and used as input. The first step was to calculate the risk score for the main impacts of Level 2 by grouping all the sub-impact under the same main impact using the FIS. The sub-impacts risk score at Level 3 is considered as a triangular fuzzy number (TFN), which can then be mapped onto the developed FIS for the main impacts (Level 2 FIS). In the second step, the same method was used to aggregate the risk score of Level 2 which is the risk score of the main impact in order to calculate the total risk score of the proposed elective change at Level 1. To develop a Level 1 FIS, the steps described below were taken:

1) Define the Financial, Operational, and HSE impacts using linguistic terms. Each main criterion was defined using TMFs that cover each main criterion universe of discourse. To outline the linguistic terms for each main criterion, several meetings were held with the senior risk analyst; 2) Develop each criterion MFs. In the course of this process, the senior risk analyst was consulted to define 5 MFs. Then, the TMF shape was chosen; as mentioned earlier, TMF is a system intuitive to expert opinion and is good enough to describe the main criteria variables precisely. To define each MF range, the direct method with one expert (Klir and Yuan, 1995) was used. 3) Capture expert knowledge after identifying the MFs for the inputs and output variables in order to define the relationship between the inputs and output for FIS Level 1.

As previously shown, any fuzzy “IF-THEN” rule has two sections. The first section shows the different main input impact combinations, while the second part shows the output based on the input impact interaction. Since there are three inputs for Level 1 FIS and each input can be shown by using five linguistic variables, 125 rules (5^3) were generated to cover all possible combinations similar to Level 2 and 3 FIS, the centroid defuzzification approach was selected and “Max” and “Min” operators were selected for aggregation and implication respectively due to their straightforward graphical clarification and wide applicability (Jang, 1996; Jang et al., 1997). 3D output surface views were used to show the sensitivity of the output variable based on the changes of two selected input variables for the developed FIS, as shown in Figure 4.12. These surfaces help in understanding the changes of the output versus the input variables and mitigate the inconsistency in capturing expert knowledge.

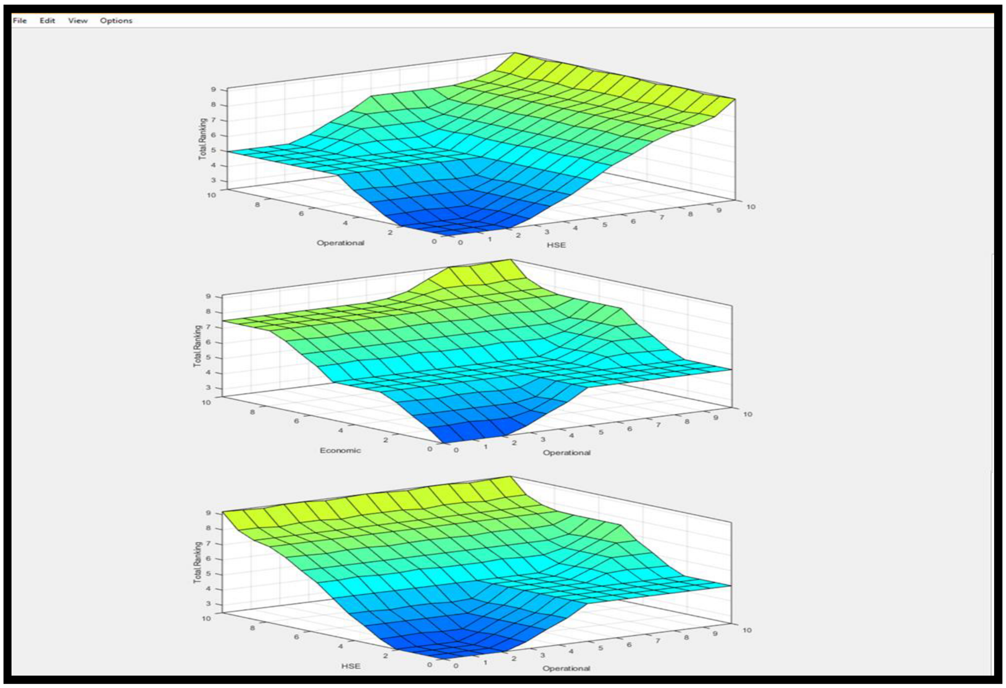


Figure 4-12. 3D Inputs and Output Surfaces.

Note here that, when assessing the risk score of impacts associated with changes, companies usually consider the controllability factor, which has not been considered in the risk quantification calculations. However, the effect of controllability is usually reflected in the “impact level” and “occurrence probability” ratings. If a risk score associated with a proposed elective change is within the control of a company or can be shifted to other parties by incorporating clauses for this purpose in the contract, companies can assign a lower risk rating based on the controllability factor.

4.2.3 Change Approval

Any changes should go through a formal authorization procedure (Figure 4.13). For this purpose, there are a set of predefined procedures in the general conditions’ sections of any construction contract type. After the proposed change has been reviewed by all parties, owner/client permission is obligatory for the change to be finalized. At this point, a change can be accepted, modified, or rejected. An approved change will modify the scope of work agreed upon in the contract. On the other hand, although a rejected change should be disregarded, it should be registered in the project database for the purpose of lessons learned. The approval process should be done in a timely fashion to avoid moving the changes to a later project time where they become costlier to execute. In addition, delaying requested change approval may lead to disputes and claims jeopardizing the completion of the project. Change approval is defined as an authorization made by the management team and should be considered a high priority. A sound change management model should be able to keep records of all existing facts by involving all parties. This approach helps ensure that all the information regarding changes will be easily retrievable at any time for future use. At this stage, the model should be able to notify all parties involved and track all the activities related to the imposed changes to make sure that changes are done according to the agreed-upon plan.

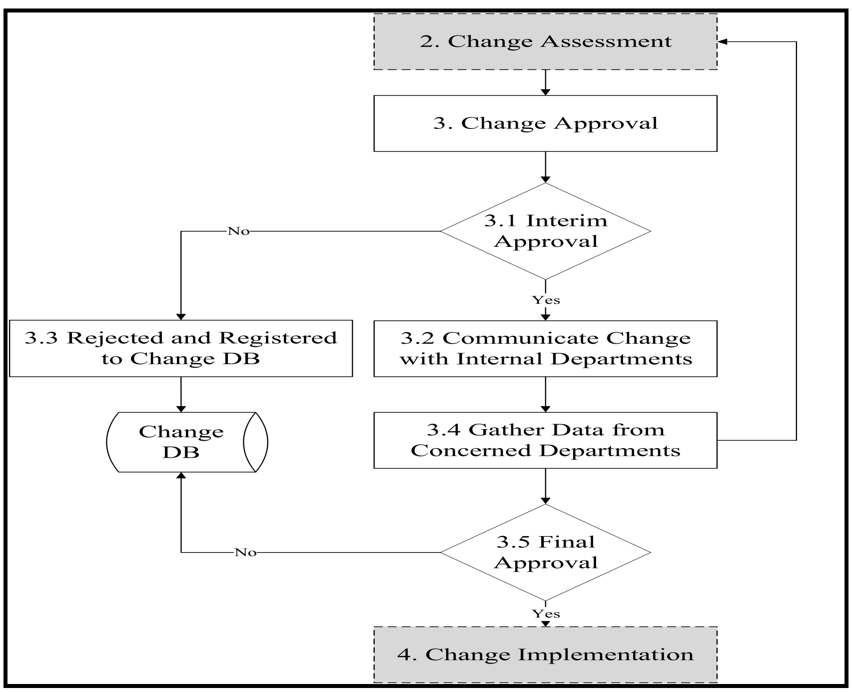


Figure 4-13. Overall Change Approval Process.

4.2.4 Change Implementation

Change implementation is a crucial step in any change management process because this is the main reason for a sound change management model. It is highly recommended that no work related to a change be conducted without written authorization. In the construction industry, it is not uncommon that the change is still in the approval process despite the fact that it has been implemented. This is because of the fast-paced nature of construction projects and the need to complete the change. In this case, a change may lead to other problems and additional changes because the management team has not communicated with all the parties directly or indirectly impacted by the proposed change. It is very important that change orders be tracked as it helps monitor how the change is being implemented and allows the project management team to resolve any issues that might arise during the implementation stage. In addition, monitoring and tracking changes will allow the project team to capture and document crucial change information so any later disputes can be settled easier and the lessons learned can be used for comparable situations in the future. Comprehensive change information should be recorded from initiation to closure so that this information may be utilized to provide historical data on current and future projects. The graph below shows the general change implementation process (Figure 4.14).

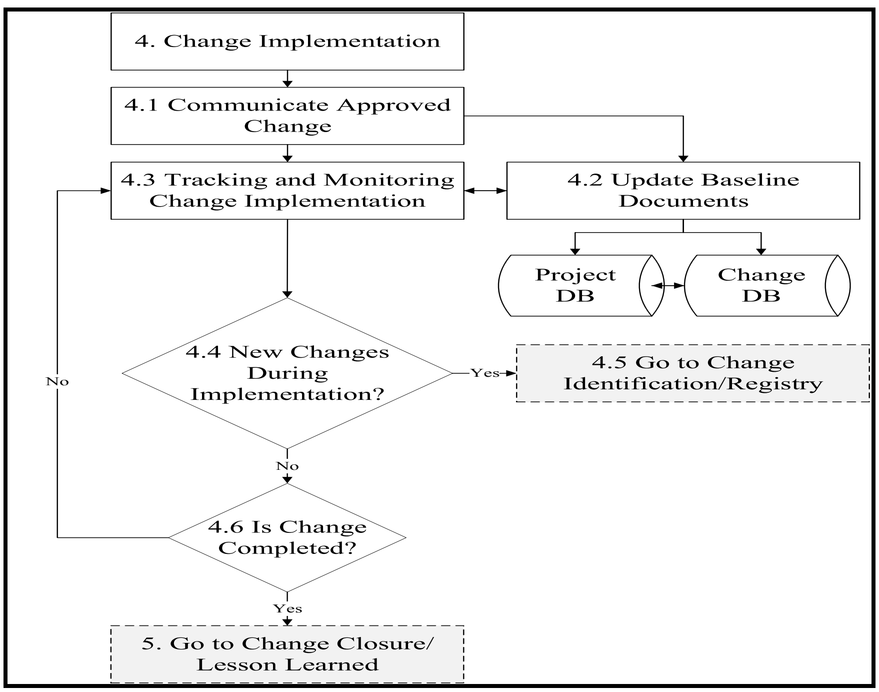


Figure 4-14. Change Implementation Process General Overall View.

4.2.5 Change Closure and Lessons Learned

Same as for the approval process, change order closing and handover requires a formal procedure after a change has been executed. A client should approve a change and its implementation according to the agreed-upon plan and this step is required for compensation. In addition, post analysis of lessons learned should be recorded for future use (Figure 4.15). By performing Root Cause Analysis (RCA), the project management team should be able to identify a comprehensive list of change root causes with the HSE, Operational, and Financial impacts. RCA results should then be discussed with team members to avoid repeating similar mistakes in future projects. RCA helps to answer three questions: 1) what happened, 2) why it happened, and 3) what to do to in the future to decrease the probability of issue occurrence. It is worth mentioning again that documenting lessons learned will help the project management team deal with future change issues in a proactive manner (Ibbs et al., 2001).

4.3 Developing the FRCM Computerized Prototype

Current practices in change management highly depend on professional judgment. The developed FRCM model attempts to provide decision-making support to the project management team by offering comprehensive information on proposed changes during the course of a project, from initiation, to commission, to the handover phase. Standalone commercial change management system software is rare. These change management systems are available mainly as commercial project management software modules. In addition, commercial software mostly focuses on information flow and record keeping and does not facilitate the decision-making process while accepting and rejecting changes.

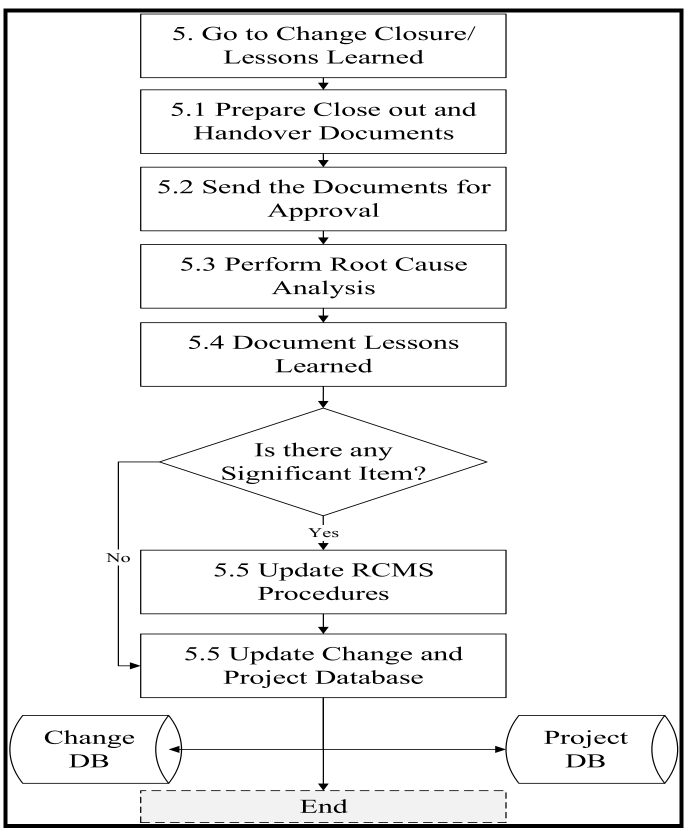


Figure 4-15. Change Closure and Lessons Learned General Overview.

The change management model developed here is an effective model because it: 1) Gathers and integrates all project and change information, contains causes, indications, bases, impacts, and processes for managing changes; 2) Identifies and assesses all areas impacted by a change throughout the design and construction phase; 3) Automates workflow for change review, approval, and execution; 4) Facilitates the decision-making process by employing the fuzzy-based risk ranking model; 5) Informs project parties by sending notifications, reminders, etc. 6) Records day-to-day activities and incurred cost; 7) Facilitates claim and dispute resolution by keeping records of project documents such as correspondences, estimates, and technical documents from various electronic systems; and 8) Identifies consequential changes and presents data ready for performing cumulative impact analysis. The developed model has six major components along with several sub-components as follows (Figure 4.16):

1. Change registry module: a) Entering project details and b) Entering change details;
2. Change assessment module: a) Cost assessment, b) Schedule assessment, and c) Fuzzy-based risk assessment for elective requested changes;
3. Consequential changes identification module;
4. Requested change e-approval module for elective changes;
5. Comprehensive reports regarding daily tracking of change orders; and
6. Project dashboard module: a) Number of primary change orders in terms of elective and mandatory change orders, b) Number of consequential change orders in terms of E&I, mechanical, architectural, and structural changes, c) Number of new change orders, d) Number of approved elective change orders, e) Number of pending change orders, and f) Number of rejected change orders.

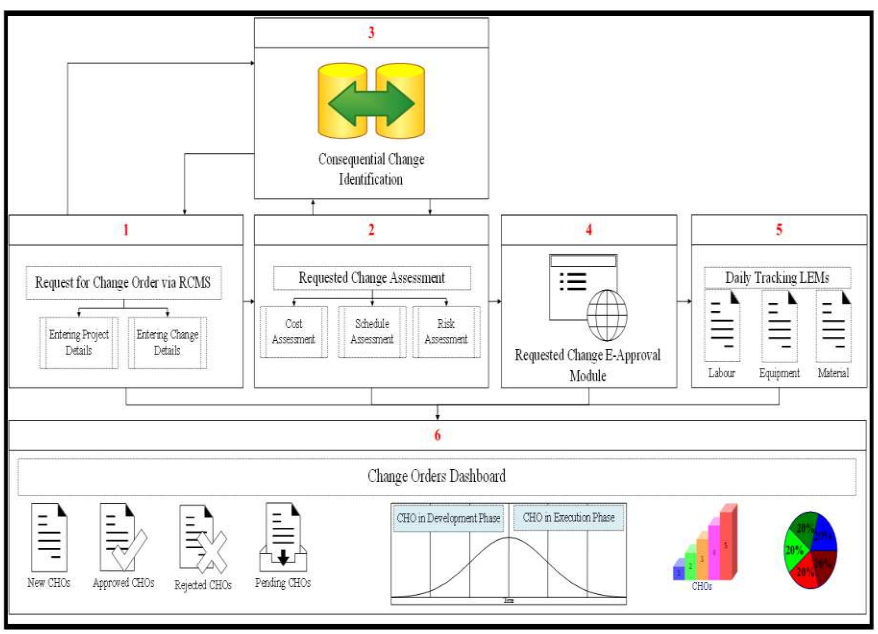


Figure 4-16. General FRCM Model Architecture.

As mentioned earlier, the developed computerized prototype offers structured record keeping for project changes and helps with a better assessment of any requested changes in a subjective approach. This is accomplished by providing prompt access to change information and by utilizing a structured method to inform all concerned parties in a timely fashion of the change, as well as by providing a way to encourage positive and discourage negative and unnecessary changes. However, the developed prototype cannot be used as a replacement for professional judgment.

To run the developed prototype, first, the user should log in through the graphical user interface (GUI) using the username and password assigned to her/him by the system administrator. This approach is a security feature that controls how users and the developed model communicate and interact. The GUI of the developed model was designed following user interface design principles such as ensuring appropriate visibility and pertinent consistency among various components, along with immediate feedback from the interface. Here, users will already profit from a well-developed model in a robust, aesthetically designed framework that effectively controls all its modules. The login window operates as the main access to FRCM model, as shown in Figure 4.17. It is important that different levels of access be provided to distinct types of users such as, internal user, contractor, sub-contractor, etc. The developed prototype has six modules; the modules are a key step in the effective development of prototype that meets the proposed methodology for managing changes. In addition, the developed prototype has standard features such as maximizing, minimizing, and closing the application. Figure 4.17 illustrates the main log-in screen.

Figure 4-17. FRCM Graphical User Interface (GUI).

4.3.1 Project Details Module

This module is used to facilitate project data entry. PHP and MS Access databases were used to design a web-based platform for filling different forms. After entering the username and password, other modules become available to the user. The purpose of this form is to capture projects details used as historical data for future assessment (Figure 4.18). The first step is to select the project contract number from the drop-down menu, which shows all the project contracts numbers recorded in the database. If the project exists in the database, the remaining fields are automatically filled. If the project is new and the user has authorization to add new projects, the user needs to enter the contract number and to select the project type from the dropdown menu which includes Residential and Commercial; Sports Facility; Infrastructure; Health Care; Industrial; and Educational. After selecting project type, the user enters the project name into the text field along with the project description. The description should include comprehensive information helpful to those unfamiliar with the project. In addition, other essential information needs to be added to this module such as planned start and finish date of project, project manager information, and project schedule ID number.

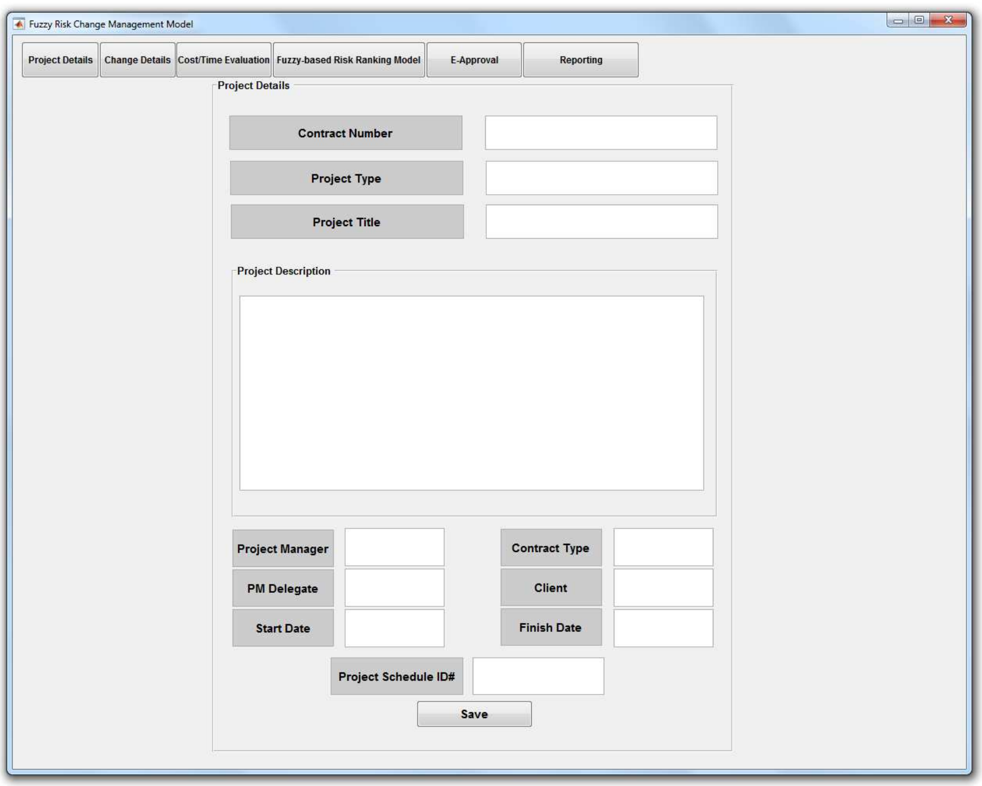


Figure 4-18. Project Details Modules.

4.3.2 Change Details Module

After retrieving or adding project details, the change order module will be activated for the user. Two options are available at this point. First, the user can modify or view existing changes by selecting them in the “Change Order Log” and all the “Change Details” information will be retrieved from the change database. The second option is to add new changes and here, the user would need to enter the requested change information in the designated area, as shown in Figure 4.19.

This module is a major component of the FRCM model and was designed to capture key information regarding the proposed change. The first step is to assign a change number to the proposed change, which is a primary key in the developed relational database. The next step is to select change type, mandatory or elective, from the dropdown menu. A comprehensive change description, as outlined in previous sections, should be added in this module. Once change type has been selected, it is important that the major discipline of the proposed change be identified, e.g. mechanical, structural, electrical, architectural, administrative, etc. Next, the user should select the area affected by the change such as super-structure, foundation, and laydown area. It is important that the proposed change be complemented with supporting documents. For example, if the change is based on an Engineering Change Notice (ECN), Non-Conformity Report (NCR), or a Request for Information (RFI), these number(s) should be entered into the designated field. The next requirement is to determine the dates the user expects the change to start and finish. These dates should be entered into the model prior to sending the change for approval. Now, with the help of the planning department, the user should identify if the proposed change has a schedule impact or not. If there is a schedule impact, the impacted activity or activities’ ID should be added into the designated field. After entering the proposed change’s general information into the model, the user should select the cost and time evaluation tab to define required resources for performing the change in the change assessment module (Figure 4.19).

4.3.3 Change Assessment Module

This module was designed for estimating resources, time, and cost associated with the proposed change. The following information should be included in this module along with an estimate of the above-mentioned items: 1) Reference number for each line item: This number is a primary key for the entered item; 2) WBS code and Sub-code: These numbers should coincide with the WBS and sub-codes in the contract. This will help to identify which WBS item in the contract will be impacted by the proposed change; *and* 3) Description: The user needs to provide a detailed description of the resources (Labor, Equipment, Material, and Subcontractor) needed to perform the proposed change for each line item. The change assessment module is comprised of four components represented as follows (Figure 4.20):

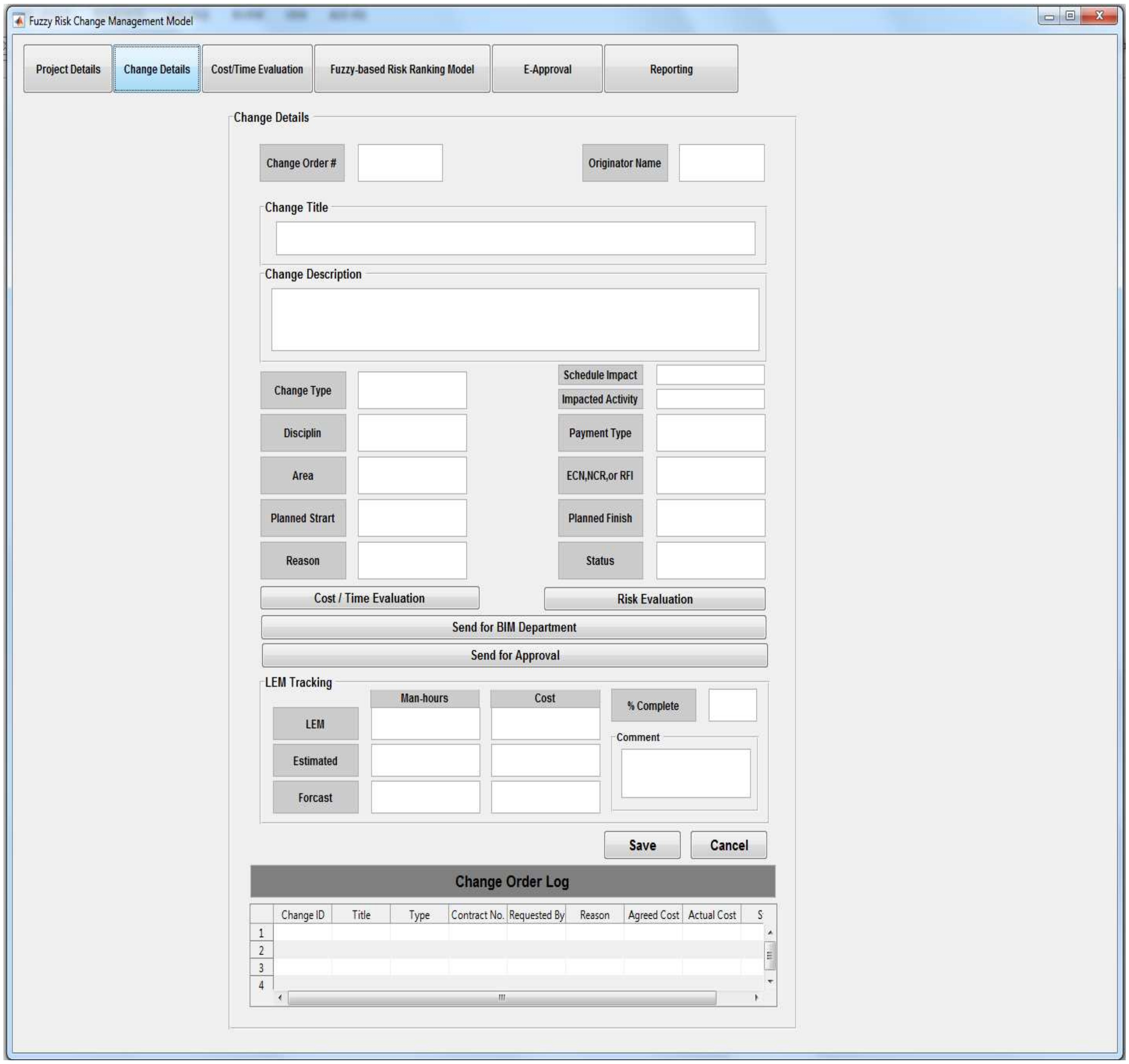


Figure 4-19. Change Detailing Module.

1) **Direct Field Labor Costs:** The user should quantify the number of DFL days and required man-hours per day for performing the proposed change. The contractor rate and mark-ups for the actual cost of the change order are based on the rates agreed on between the project parties and included as part of the project contract. Rates should include payroll burdens and elements that increase the cost of labor such as overtime have to be considered; 2) **Material Costs:** The cost of material is usually based on actual invoiced costs, or quoted costs that are received from material suppliers including an agreed-upon markup, overhead, and profit

percentage. The user can obtain this information from suppliers or from published cost guides such as RSMeans; 3) **Equipment Costs:** The equipment used for a change order can include rental or owned and will be the basis for estimating equipment costs. Usually, the rates for owned equipment are included in the contract. Rates can also be obtained from rental firms or estimating publications. Small tools and consumables costs are typically considered a percentage of total direct cost; 4) **Sub-contractors:** If a proposed change order needs to be executed by a third party, the third-party quotation or estimate should be attached to the detailed estimate. An additional percentage should be applied to cover supervision, administration, and profit. The user should include a percentage of the total direct cost as overhead to cover home office costs for the proposed change. The overhead percentage should be agreed upon and referred to in the contract; usually, it is between 8 to 15% Profit is calculated as a percentage of indirect and direct cost and typically does not exceed 10%. Consider that quantified time and cost in the change assessment module can facilitate the time impact assessment. This estimate can be used to develop a fragnet schedule for the proposed change and measure the impact of a given change on the project schedule.

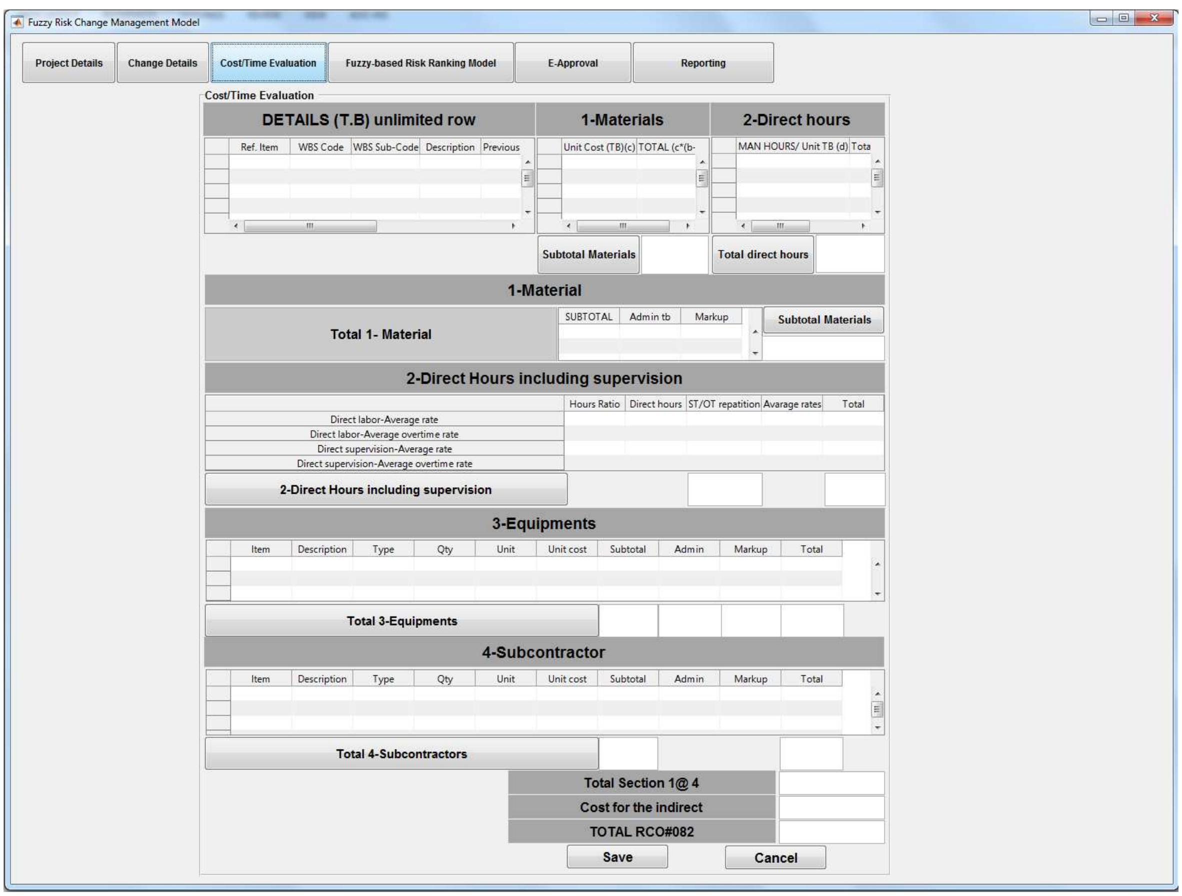


Figure 4-20. Cost and Time Assessment Module.

4.3.4 Fuzzy-based Risk Ranking Module

Two proposed options for ranking changes were used as part of the developed change management prototype. The module was developed using MATLAB. The purpose of the change risk score ranking is to facilitate the decision-making process by promoting positive changes and discouraging negative ones (Figure 4.6). This module is based on the fuzzy logic rules developed in Section 4.2.3, in which the user must assign fuzzy numbers to occurrence likelihood and consequence level of sub-criteria change impacts; these fuzzy number values fall within the range of 0 to 10. The module calculates three risk scores, namely: sub-impact risk score, main impact risk score, and final change risk score. The module also offers the option of manual risk score ranking, where a manager can revise a ranking score and add a justification for the new ranking. In addition, two proposed aggregation methods for combining the global and local weights estimated from FAHP and the developed FIS were included in the final change risk score calculation (Figure 4.21).

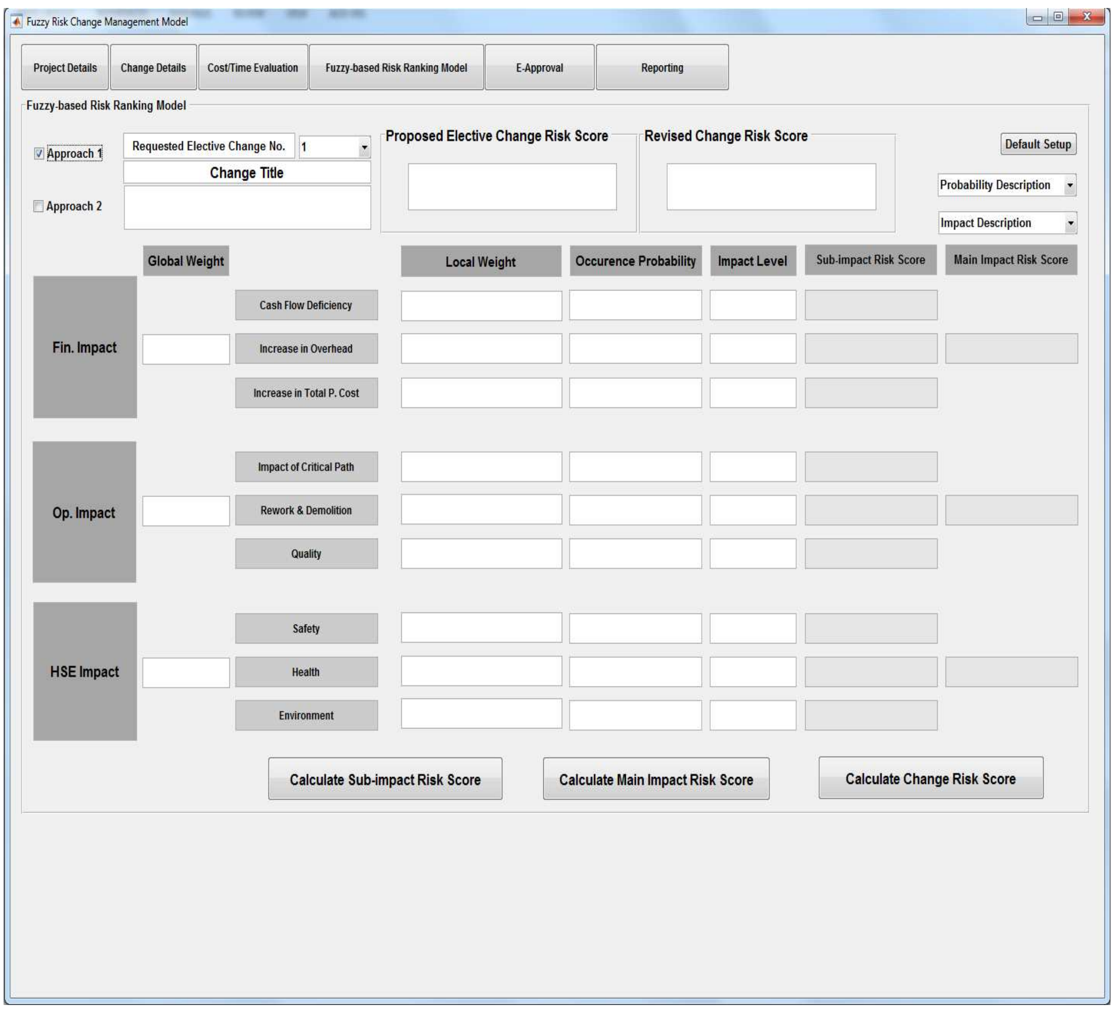


Figure 4-21. Change Order Ranking Module.

The default value for global and local weights was estimated by using the F-AHP technique, as summarized in Table 4.4. Here, the user can also assign different weights based on change and project characteristics. The user can recall the default values by using the "default" button at any time.

4.3.5 E-Approval of Requested Change and Early Warning Notification Module

After the user has completed the above steps, a change order should be sent for the process of approval. This module includes two primary features: change notification and change approval. The change notification and approval processes described here were developed for a mega project in Canada with a value of two billion dollars. However, the developed process can be adapted to any project. The purpose of the developed procedures is similar to any change management procedure and is intended to ensure that: 1) The proposed changes are professionally communicated through the right channels, efficiently recorded and easy to recall at any time during the course of a project, and approved or rejected; 2) The proposed change should contain sufficient and adequate information and supporting documents for purpose of approval by decision-makers; and 3) The proposed change consequential impacts on other project components should be addressed properly. The change management notification and approval process are described in Figure 4.22. The process was developed in a simple and straightforward manner to make it logical and practical. As mentioned previously, the originator is responsible for change initiation, making the initial assessment, and preparing a detailed justification for the change. However, this is a counter-productive feature, considering the amount of work assigned to the originator. The developed model overcomes this drawback by implanting an e-approval and early warning notification system. The e-approval and warning system is part of the developed prototype available through the e-approval module. The e-approval process allows the user to formalize his/her change requests according to the organization's change management policy. Generally, the approval process is done manually and requires physical signatures on paper from one approver to another. This manual process is time consuming and leads to serious issues in any construction projects when "time is of the essence." It is not unusual for changes in construction projects to be executed prior to the the completion of the approval process due to the fast-paced construction environment. With the proposed e-approval process, the approval time is reduced because a change order's approval email is automatically sent to individuals identified as approvers within the organizational procedure. Figure 4.22 illustrates the general overview of the e-approval module.

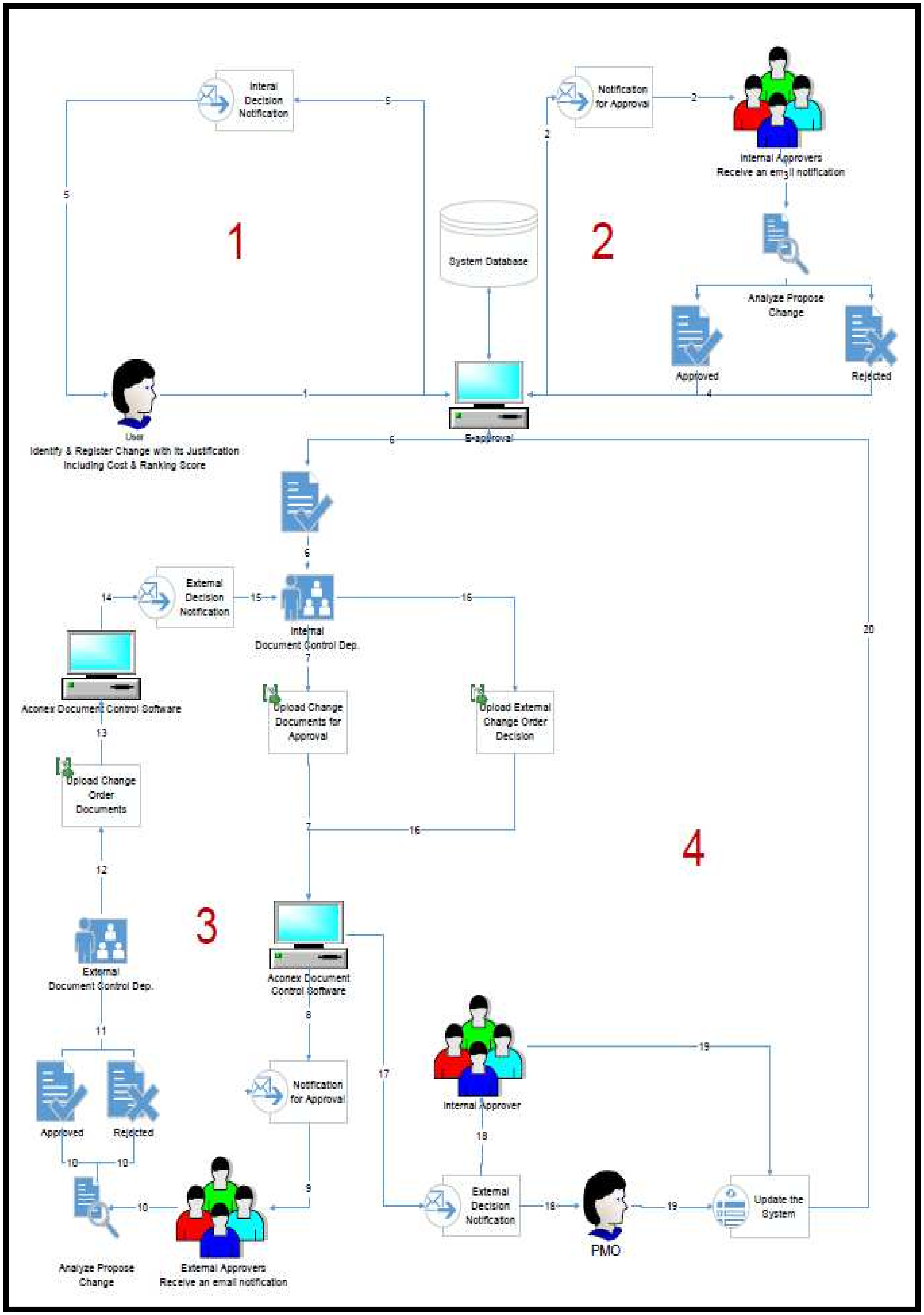


Figure 4-22. E-approval Process Overall View.

Figure 4.22 shows the steps for the external approval process using Aconex document management software. Aconex offers many outstanding options to organizations that need quick access to current project documents such as BIM models, QA/QC reports, schedules, and more. Aconex is not a change management software; however, coupled with a robust change management system, it can be an advantage to any construction project. Steps 3 and 4 of Figure 4.22 demonstrate the external approval process. An external approval process that is owner-related is not within the scope of this research. The e-approval GUI is shown in Figure 4.23. Another feature of the developed prototype which notifies the project management team regarding the status of changes is the early warning system. For instance, if a team member registers a new change request or if any major decision, approval or rejection, has been made to a change in progress, the model automatically sends a notification to the project management team regarding the new change request.

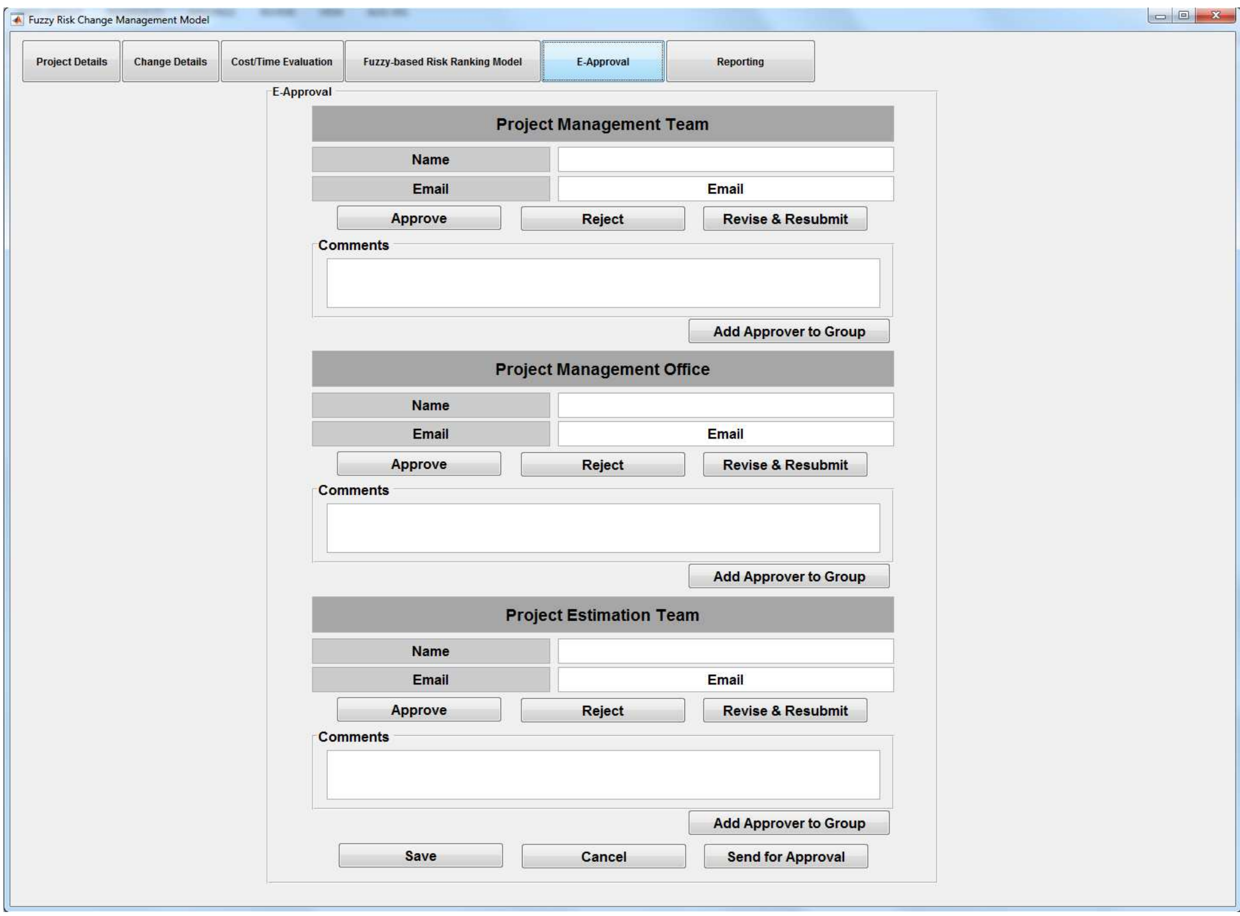


Figure 4-23. E-approval Module GUI.

4.3.6 Reporting Module

This module produces the model output reports. The user can generate different report types to depict changes as per different criteria (Figure 4.24). The reports can be seen in two ways: a web-page report or in PDF format, which allows the reports to be transmitted to the project management team via email (Figure 4.25).

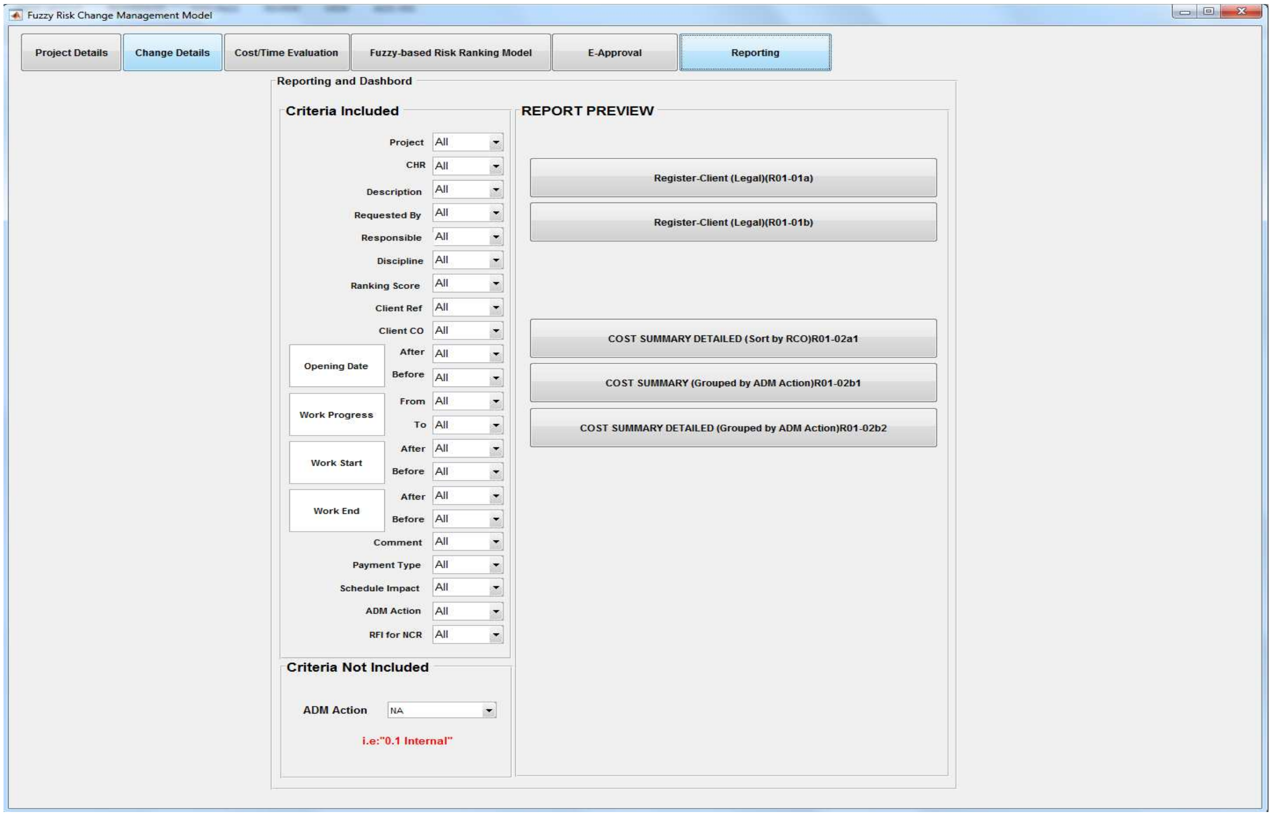


Figure 4-24. Reporting Module GUI.

GENERAL INFORMATION									MONETARY INFORMATION					
RCO #	Description	Discipline	Sector	Cient REF	Cient CO	% Progress	Start	End	ADM Action	Payment Type	Schedule Impact	Mhrs PPEC	Amount PPEC	Amount Client
PROJECT: KECS 9.2 6085 - CONVEYORS														
RCO-106	NCR-006 Slotting holes in the conveyor frame to allow for alignment on the carry rollers	STRUCT	CDC - SBFC	FCD-KECS-012	CVCO-02	100%	11/19/13	11/19/13	3.4 Agreed and invoiced	LEM	Yes	45	2,243	4,279
RCO-110	Loading Material for Krupp	STRUCT	CDC - SBFC	FCD-KECS-008	CVCO-03	100%	11/23/13	11/23/13	3.4 Agreed and invoiced	LEM	Yes	4	628	628
RCO-111	CANCELLED	STRUCT	CDC - SBFC			0%			5.1 Cancelled	Lump sum	Yes			
RCO-115	Unloading wrongly delivered material	ALL	CDC - SBFC	FCD-KECS-009	CVCO-03	100%	11/24/13	11/24/13	3.4 Agreed and invoiced	LEM	Yes	9	976	976
RCO-121	NCR-014 Obstruction between the trusses clevis brackets and the bent trusses	STRUCT	CDC - SBFC	FCD-KECS-013	CVCO-02	100%	11/30/13	11/30/13	3.4 Agreed and invoiced	LEM	Yes	20	2,067	2,067
RCO-122	NCR-011 Return roller is touching brace member for Module 24	STRUCT	CDC - SBFC	FCD-KECS-014	CVCO-02	0%			3.4 Agreed and invoiced	LEM	Yes	45	5,740	5,740
RCO-126	INTERNAL: NCR-013 Replacing damaged Tech Electrical cable onto Drive pulley cleaner #4 motor.Equipment# 2110-112-M-1043-The damage is shipping damage	ELECT	CDC - SBFC			100%			0.1 Internal	Lump sum				
RCO-141	Cancelled	MEC	CDC - SBFC			0%			5.1 Cancelled	LEM				
RCO-142	NCR-010 Received Module # 22 (Surge Bin Feed Conveyor) with Bent Leg.	STRUCT	CDC - SBFC	FCN-KECS-015	CVCO-03	100%			3.4 Agreed and invoiced	Lump sum		9	941	941
RCO-143	NCR-009 Received Module # 24 (Surge Bin Feed Conveyor) with Bent Leg.	STRUCT	CDC - SBFC	FCN-KECS-016	LOT 03	100%			3.1 Agreed awaiting CO	Lump sum		9	941	941
RCO-144	NCR-008 Missing holes in column 5109 to connect rap plate 5437	STRUCT	CDC - SBFC	FCD-KECS-019	CVCO-03	100%	03/13/14	03/13/14	3.4 Agreed and invoiced	LEM		11	1,178	1,178
RCO-158	INTERNAL: Shut down due to severe cold weather 2013-12-07	ALL	Common			100%	12/07/13	12/07/13	0.1 Internal	LEM			21,480	
RCO-167	INTERNAL: Employee appreciation day-PPEC	ALL	Common			100%	12/15/13	12/15/13	0.1 Internal	LEM		56	9,385	
RCO-185	INTERNAL - PRESERVATION- SBF conveyor	STRUCT	CDC - SBFC			0%	01/13/14		0.1 Internal	LEM				
RCO-214	CANCELLED					0%			5.1 Cancelled	LEM		36	4,135	
RCO-226	RFI-25: Cut and reweld stiffener as per the new welding details from Krupp			FCD-KECS-020	CVCO-03	100%	02/23/14	03/03/14	3.4 Agreed and invoiced	LEM	Yes	58	6,432	6,432

Figure 4-25. Generated FRCM Report Sample (RCO to be changed by CHR).

4.4 Developed Database

The FRCM model includes the development of two relational databases, namely, “Project” and “Change” databases. The “Project” database stores general information regarding the project such as employees, planned and actual budget, and planned and the actual date. The “Change” database stores all the information required for managing and evaluating a change such as the reason for the change, required resources, and planned date. Upon project completion, all the information registered in the “Project” and “Change” databases is then transferred to the “Historical” database. All the databases are stored in the database server. The developed databases cover a well-defined change management scope to track and control individual change during the course of a project. Thus, the data structure is crucial to the development of a robust database. Entity-Relationship (ER) modeling (Chen, 1976) was used to illustrate and formulate project data, as shown in Figures 4.26. to 4.29. Entities, relationships, and attributes are three major components of an ER diagram. The entity, in relation to a database, can be defined as an object in a system that should be modeled by the accumulation of its related information. Four different relationships were used in the database design: One-to-One (1:1), One-to-Many (1:M), Many-to-One (M:1), and Many-to-Many (M:M). Attributes represent the characteristics of entities. The following different attribute types were used in the developed databases: single valued, multi-valued, compound/composite, simple, and derived attributes. Single valued attributes are those attributes that are singular for an entity, for example, a person cannot have more than one age value. Single valued attributes are used to identify change code, name, and resource. Multi-valued attributes are those attributes that can have multiple values for the same entity such as cost, actual hours, and material quantity. Compound or composite attributes can be divided into two or more attributes such as change order total cost, which can be divided into labor hours and material quantity costs. Derived attributes are those that can be derived from other stored attributes such as change percentage. In addition, each entity has a unique identifier known as a primary key. A primary key can be a single valued or compound attribute. To make sure important data was considered without any interference between entities and relationships, ER diagrams were developed to serve as a reference model.

4.4.1. Project Database

The “Project” database is one of the main databases of FRCM model and is designed to organize and store all general information and data captured from construction projects. The “Project” database was developed conceptually using 21 entities or tables (17 physical and four conceptual) and 22 relationships. Physical entities include “Company, Employee, User, Project, Planned Budget (Labor, Material, Equipment, and Sub-contractor), Actual Cost (Labor, Material, Equipment, and Sub-contractor), Distribution, CContract (Client Contract), and SContract (Sub-contractors Contract).” These entities record general information such as the name of projects, employees, planned budget, and actual cost for Labor, Material, and Equipment. “Labor” entity captures the DFL personal information. One major attribute of the “Labor” entity is the trade, illustrated in Figure 4.26. Trade matches the union corresponding to the labor such as Carpenter or Concrete Union. “Planned Budget” shows the amount of money available over a period to meet project objectives. “Actual Cost” shows the amount of money spent on a specific thing to meet the project objectives. “Distribution” shows the “Planned Budget” distribution to different resources and scope of work. “CContract” and “SContract” entities show the type of contract, contract ID #, and the total value of a contract between “Client and Contractor” and “Contractor and Subcontractor.” Four conceptual entities in the ER diagram are for the purposes of saving external information: “PStatus,” “PCondition,” “PChanges,” and “Interface.” The “PStatus” entity shows the project completed percentage. “PConditions” records daily site condition including weather conditions and site incidents. The “PChanges” entity records any changes that may occur during the lifecycle of a project. The “Interface” entity records any information related to congestion, over stacking, delay, and distribution. There is a 1:1 relationship between “Project” and “CContract” as well as between “Employee” and “User.” This means that a project can only have one contract name and ID, and Client and employee can have only one user ID in the system. A one-to-many relation exists between several entities as can be seen in the ER diagram such as “Company-Project”, “Project-Planned Budget”, “Planned Budget-Distribution” etc. Meanwhile, the relationship between “Planned Budget” and resources including “Labor”, “Material”, “Equipment” and “Sub-contractor” is Many-to-Many; These resources can be used by other entities and these relationships are the same for “Actual Cost” and “Resources.” Figure 4.26 illustrates some of the attributes. The arrows in Figure 4.27 illustrate the dependencies between entities; for example, “Project-PCondition” demonstrates that the “PCondition” entity is dependent upon the existence of “Project,” but “Project” is not contingent upon “PCondition.” Consequently, the involvement of the “Project” entity is considered a partial contribution, while the involvement of dependent entities is considered a total contribution. In the developed ER diagram, “PChanges,” “PStatus,” “Interface,” and “PCondition” are all weak entities. Weak entities are those which cannot be fully identified by their own attributes and require a foreign key in combination with their attributes to create a primary key. The database was developed using Microsoft Access 2017, as shown in Figure 4.26. The Figure 4.27 show the entities and their respective relationships and attributes.

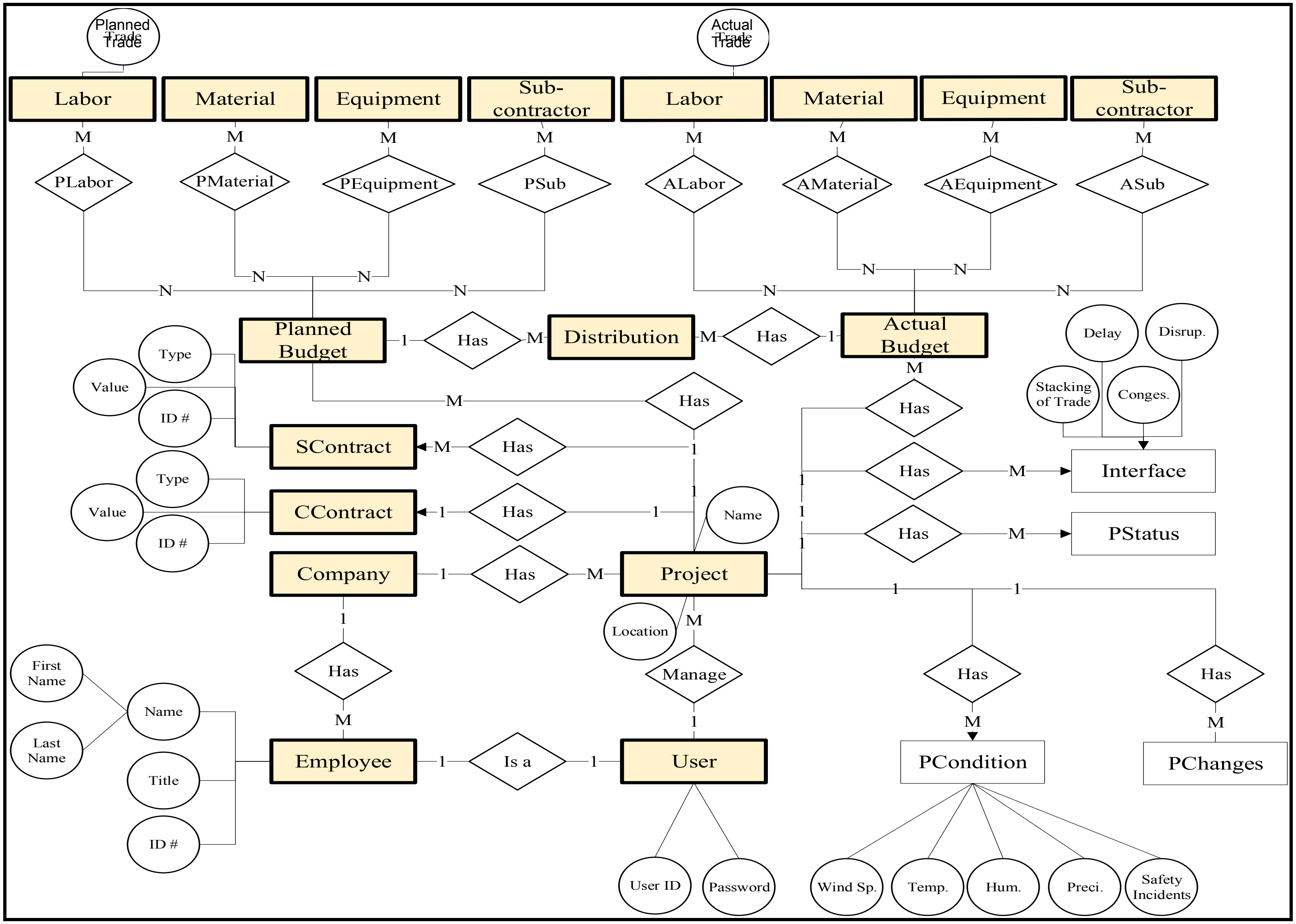


Figure 4-26. Project Database ER Diagram.

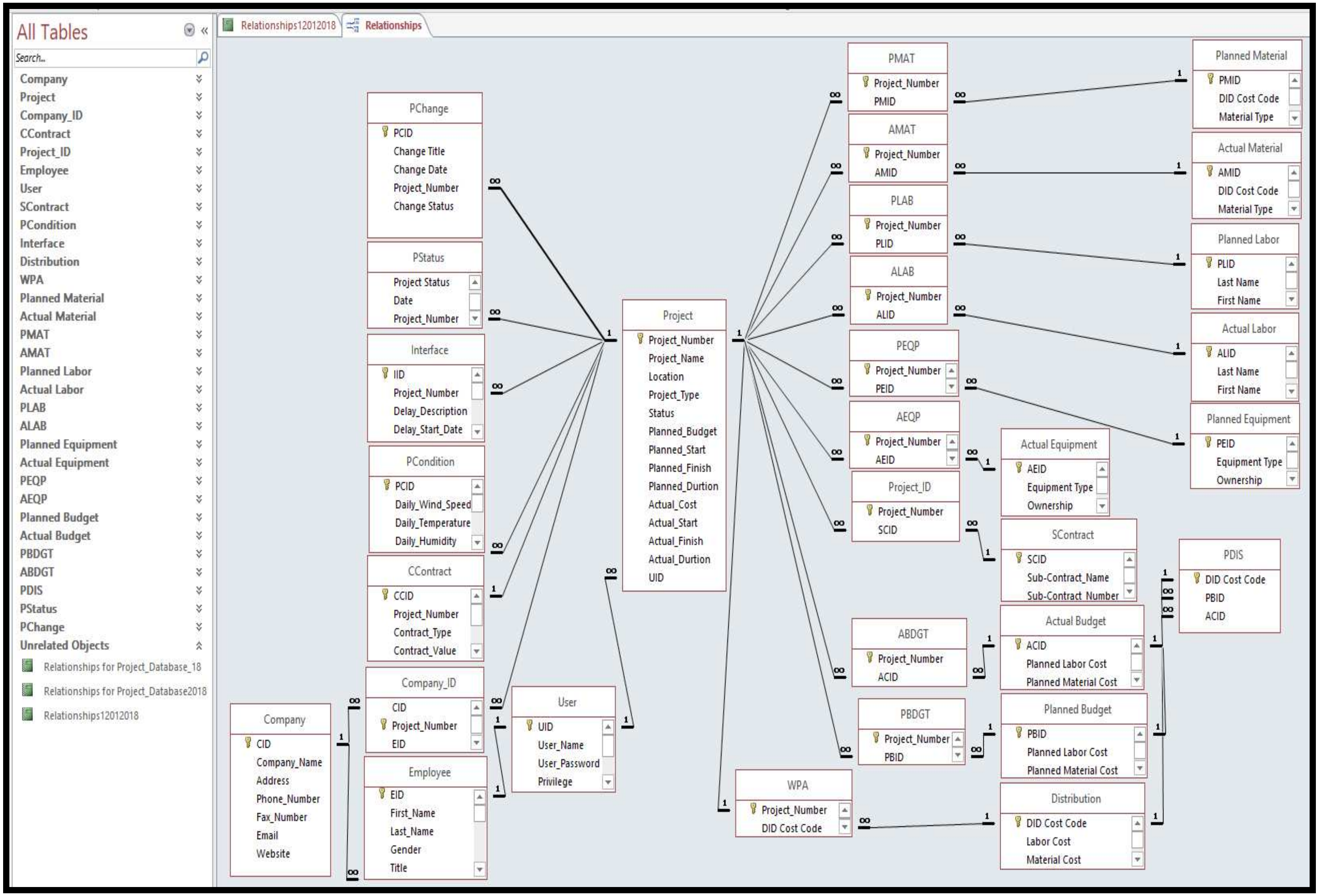


Figure 4-27. Project Database Entities and Relationships.

4.4.2. Change Database

Change management highly relies on information. Optimum change management requires that a considerable amount of data be stored and retrieved during the course of a project. Therefore, the "Change" database was designed and developed to support the proposed change management model. All the modules mentioned in the previous sections interact with the "Change" database. The "Change" database is designed to store, organize, and manipulate captured data regarding changes; it provides queries to recall information required for reporting changes status for efficient change management. A "Change" database ER diagram was used to design and develop the database for this purpose (Figure 4.28). The "Change" database is considered a part of the "Project" database but is only for the purpose of tracking changes. The reason for the two different databases is to allow different companies the ability to adapt and tailor for the developed "Change" database to suit their needs. The "Change" database is considered an essential part of the FRCM model, used for data analysis and reporting purposes. The developed database includes 21 entities or tables and 22 relationships. "Project" entity stores all the information related to the project such as project ID number, description of the project, and location of the project. "Change" entity records the information regarding changes such as the description of the change, originator, status, and date issued. "Type" is for recording whether the change request is "Mandatory" or "Elective." "Ranking Score" records data regarding the fuzzy-based risk ranking score as described in Section 4.2.3.

"Staff" records all the data regarding staff assigned to the project such as name, last name, and ID #. "User" recodes username, password, authorization level, date of activation, status, role, role description, and the last login date. "CStatus" records the daily progress of change received during the change execution phase. Here, the administration status of a change order is recorded under the "Change" entity. "Estimated Cost" records estimated cost for the execution of the change order.

This entity covers three main resources including Labor, Material, and Equipment as well as sub-contractor cost. "Actual Cost" records daily cost occurred for change orders. This entity captures information to generate daily Labor, Equipment, and Material report useful for compensation. "Consequential Change" records the information generated by VCD. "Reasoning" records the reasoning coding system as discussed in Section 4.2.1. The Change Database, as illustrated in Figure 4.28, is built by means of Microsoft Access 2017 software as shown in Figure 4.29.

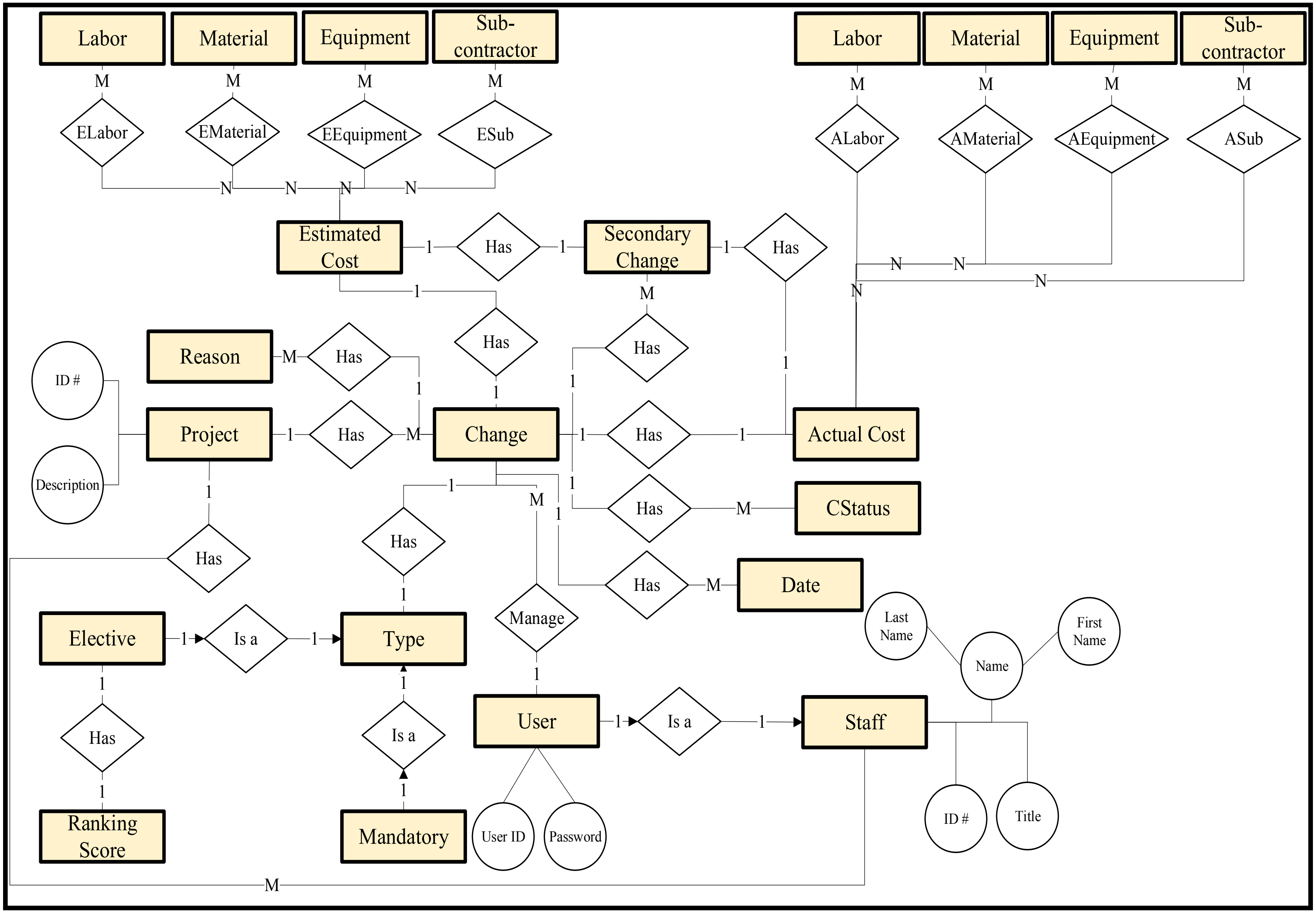


Figure 4-28. Change Database ER Diagram.

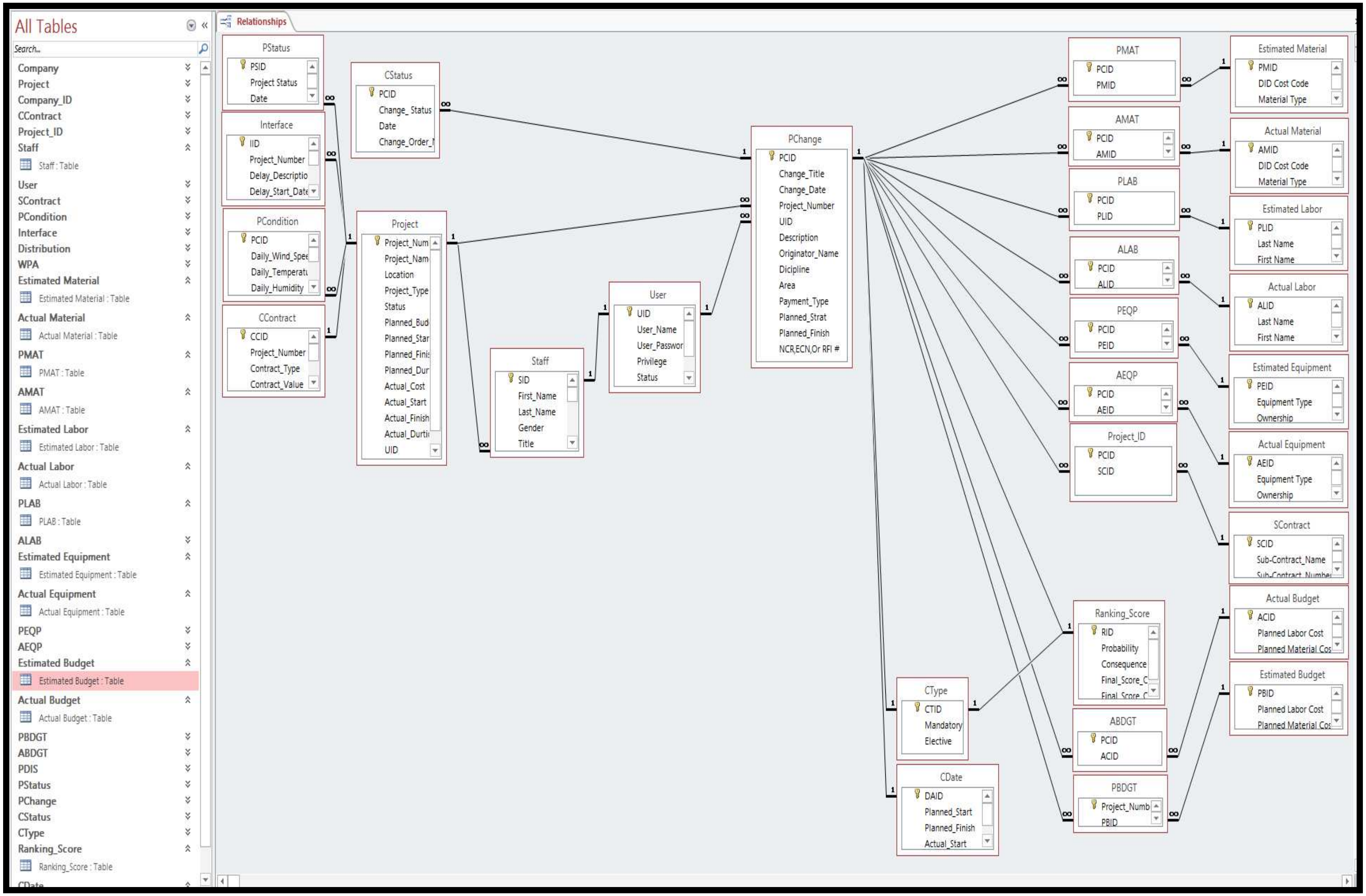


Figure 4-29. Change Database Entities and Relationships.

4.5 Summary

This chapter proposed FRCM model for managing changes over the course of a project. The FRR model was proposed and integrated into a subjective structure for change prioritization in construction projects. Fuzzy logic was used to tackle vagueness using shrouded changes assessment linguistic expression. Fuzzy rules were developed based on several interviews with risk analysts employed at one of the largest EPC/EPCM engineering firms in North America. The relative importance of sub-change impacts and main change impacts were taken into account when calculating the change risk scores. An F-AHP was used for calculating relative importance in terms of global and local weight in order to solve the multi-criteria decision-making dilemma for calculating the final risk score based on two proposed aggregation methods. The main idea behind this chapter was to provide a tool for facilitating the decision-making process for proposed changes in a way that the integration of positive changes with the project is encouraged and unnecessary changes and their negative impacts on all project aspects are reduced as much as possible. A computerized prototype was developed to incorporate the above-mentioned structures and other features necessary for efficient and effective change management during the course of a project. Two databases were designed to store project and change data along with entity relationships diagrams. These databases provide a data sharing environment for managing changes at various stages of a project. The output of this chapter was then used to develop the SD model described in Chapter 6. In Chapter 7, a real case study is applied to the developed prototype for validation

5. CHAPTER FIVE: MODELING LABOR PRODUCTIVITY

5.1. General Overview

This chapter will cover construction project labor productivity modeling by proposing an Artificial Neural network (ANN). To highlight the advantages of the developed model, several techniques were employed and compared against the developed model. The formwork dataset used for modeling labor productivity in this research was gathered by Khan (2005). Figure 5.1 illustrates the variables used to model labor productivity for formwork installation in a construction project. These variables were selected due to their daily causation of variations in productivity (Khan, 2005).

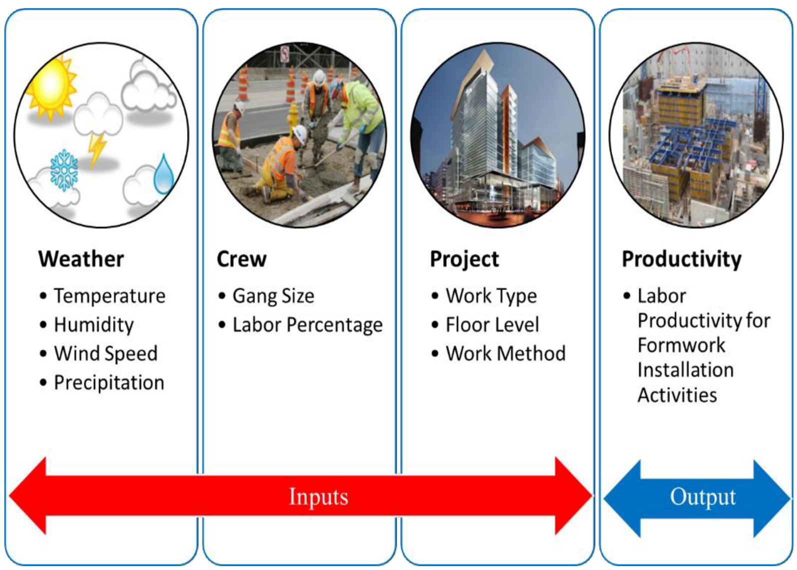


Figure 5-1. Input and Output variables.

Researchers and industry practitioners agree that changes are an integral part of construction projects and that cumulative impact of changes should not be overlooked because it can be detrimental to project success. Cumulative impact of changes on construction labor productivity is difficult to identify and measure. Although Measured Mile Analysis (MMA) is a well-known and widely accepted method for quantifying the cumulative impact of changes on labor productivity, it is not easily applicable to many cases, as not only it uses the un-impacted period of work as a benchmark, but also the un-impacted period should be long enough to represent real project productivity. It is very common that an un-impacted period of similar work simply does not exist, or the un-impacted period does not represent substantially similar activities. Therefore, identifying the un-impacted period is a challenging task since to establish the un-impacted period requires subjective judgment from an analyst. To overcome the difficulty associated with identifying the un-impacted period and quantifying Baseline Productivity (BP), an ANN was proposed and compared against several linear and nonlinear regression models and Artificial Intelligence (AI) modeling techniques. The developed models processes and procedures are described in the following sections. Figure 5.2 shows a general overview of the labor model development processes explained in this chapter.

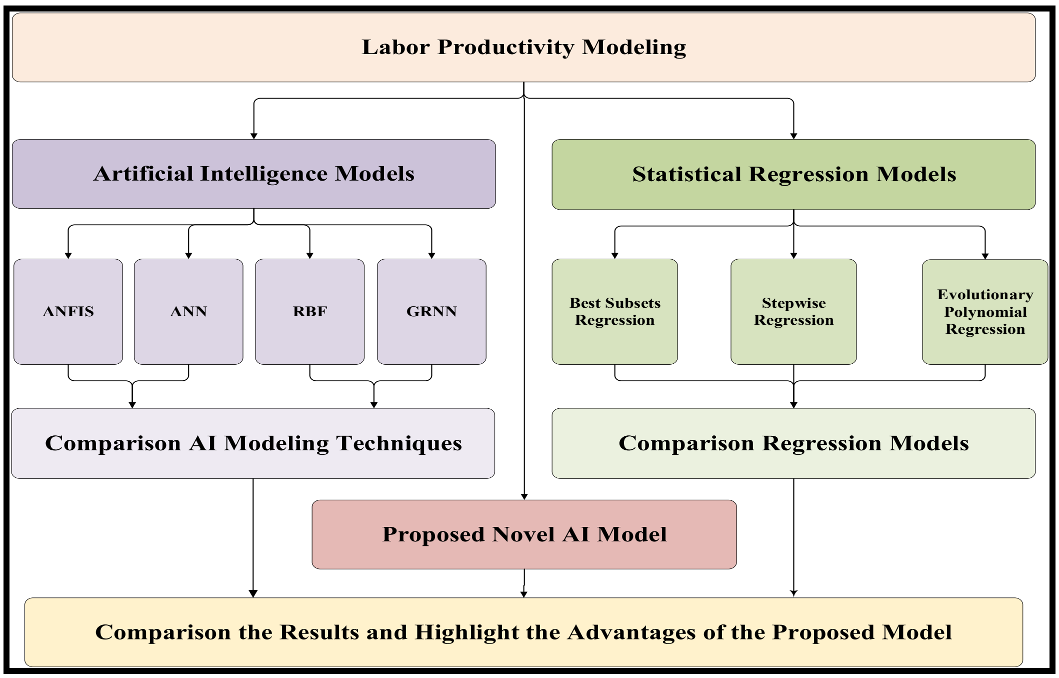


Figure 5-2. Schematic Diagram of Labor Model Development.

5.2 Productivity Modeling

Modeling labor productivity is challenging, as it requires the quantification of influencing factors affecting labor productivity and consideration of influential factors' interdependencies. Productivity modeling has been a topic of interest for many researchers and the various models being developed today can be classified into two major groups of Statistical and AI models. Regression analysis is the most common statistical method for modeling labor productivity. The main regression analysis advantage is that the productivity model can be developed to reach anticipated clarification or forecasting levels with as few predictor variables as possible. However, for regression methods, the degree of relationship (linear and non-linear) needs to be selected prior to model development. In AI modeling, NN models are the most common methods for developing labor construction productivity. Unlike regression methods, in NN modeling, the degree of relationship is not a concern. In addition, NN architecture, such as the number of hidden layers and activation functions, plays a significant role in model accuracy. In this research, all modeling techniques, including the developed model shown in Figure 5.2, were employed for modeling labor productivity based on the datasets gathered by Khan (2005), and tested for validation against a real case study. Before embarking on further elaboration of the productivity models' techniques, the next section will explain the data collection process.

5.2.1 Data Collection Background

Over a period of 18 months, Khan (2005) performed field observations and data collection from two high-rise buildings located in downtown Montreal. The first was the Concordia University Engineering and Visual Arts (EV) building, a 17-story integrated educational complex. The EV building is a concrete, mainly flat slab structure with roller compacted concrete (RCC) construction and several typical levels with a surface of 68,000 m^2. The project was constructed over three years. The second building is a similar structure system, a 16 stories building located downtown Montreal. Over the 18 months, 221 data points were collected from both projects. The following table shows a sample of the data collected (Table 5.1).

Table 5-1. Sample of Data Gathered by Khan (2005).

T	H	P	WS	GS	LP	WT	FL	WM	Productivity
-6	41	0	3	11	37	1	17	2	1.47
-1	58	0	3	12	42	1	17	2	1.58
16	61	0	3	22	36	1	13	1	2.4
-4	87	2	3.6	22	36	1	4	1	1.55
1	60	0	5	12	42	1	17	2	1.65
1	66	0	5	8	37	2	16	1	1.44
2	76	0	5	9	33	2	16	1	1.51
14	71	0	5	20	35	2	15	1	1.85
-12.5	54	0	5.2	21	38	1	3	1	1.17
-12.5	54	0	5.2	20	30	2	3	1	1.04

As can be seen from Table 5.1, three variables in Khan's datasets can be considered as qualitative. These variables needed to represented in numerical form in order to be included into the developed models: 1) Precipitation: Incorporated in terms of four numerical values assigned as: No precipitation=0, light rain=1, snow=2, and rain=3; 2) Work type: For the purposes of analysis, three types of work were coded as follows: Slabs= 1, walls=2, and columns=3; and 3) Work method: Two techniques were used at both sites as follows: Built in Place (BIP) and flying forms coded as 1 and 2 respectively.

5.2.2 Descriptive Statistical Analysis

Descriptive statistics provide a summary of the collected data. Table 5.2 shows the descriptive statistics of this research's collected data. These parameters were used to calculate some important indices like the Standard Deviation (StDev), Standard Error of the Mean (SE Mean) and Mean, which help in develop of proposed model.

Table 5-2. Collected Data Descriptive Statistics.

Variable	Mean	SE Mean	StDev	Min.	Q1	Median	Q3	Max.
Temperature	4.08	0.81	12.03	-26.00	-4.50	3.00	14.50	25.00
Humidity	66.34	1.05	15.67	18.00	56.00	67.00	76.50	97.00
Precipitation	0.28	0.04	0.60	0.00	0.00	0.00	0.00	3.00
Wind Speed	15.42	0.57	8.46	3.00	8.90	14.00	19.00	43.00
Gang Size	16.03	0.34	5.07	8.00	11.00	18.00	20.00	24.00
Labor Percentage	35.49	0.26	3.79	29.00	33.00	36.00	37.00	47.00
Work Type	1.43	0.03	0.51	1.00	1.00	1.00	2.00	3.00
Floor Level	11.38	0.25	3.75	1.00	10.00	12.00	14.00	17.00
Work Method	1.44	0.03	0.50	1.00	1.00	1.00	2.00	2.00
Productivity	1.57	0.02	0.35	0.82	1.31	1.51	1.79	2.53

5.3 Statistical Productivity Modeling

In this research, three different regression analysis methods were used to model construction labor productivity based on the collected data as follows:1) Best Subsets Regression (BSR); 2) Stepwise Regression (STR); and 3) Evolutionary Polynomial Regression (EPR).

Regression analysis is a statistical technique used to forecast and explain the causal relationship between input and output variables. In regression analysis, the output variable is named as the response variable and input variables are known as predictor variables. The response variable is expressed as a function of the predictor variable(s). Figure 5.3 displays regression modeling development.

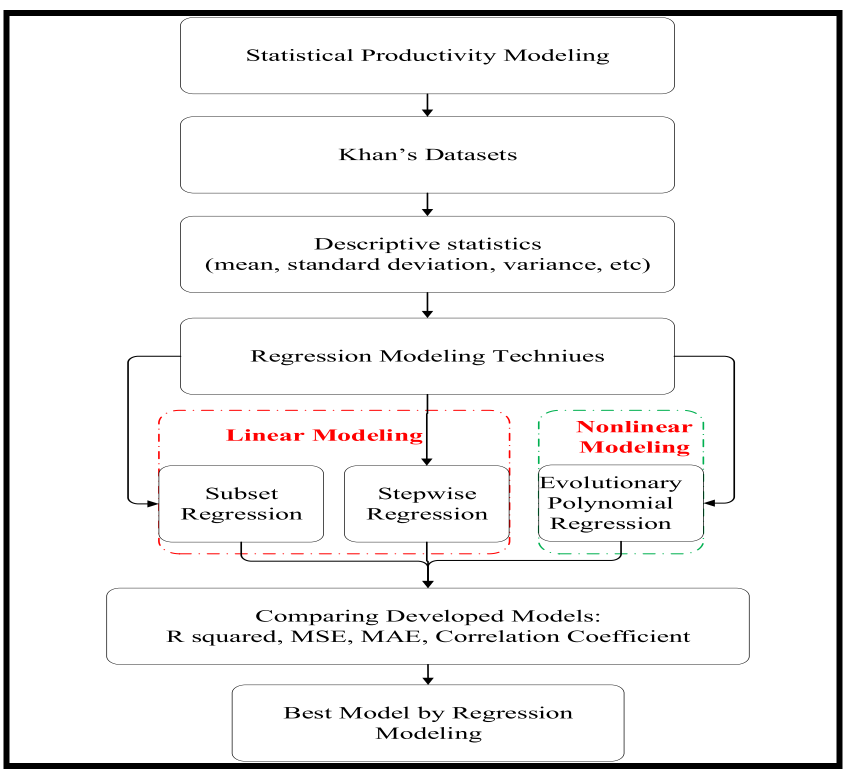


Figure 5-3. General Overview of Statistical Productivity Modeling.

5.3.1 Best Subsets Regression Modeling

The first technique employed under regression analysis is Best Subset (BSR), an exploratory modeling technique that searches for all possible models that can be developed with the given data to then finally introduce the best candidates (Minitab17, 2018). The best result will be identified based on the performance criteria of R squared, Adjusted R squared, Predicted R squared, Mallows Cp, and Mean Square Error (MSE). It should be noted that BSR is not suitable for modeling cases with a large number of variables since in these cases, finding the best combination of predictor variables will take more computational time. In this study, nine predictor variables as shown in Table 5.1 were used to predict labor productivity.

The BSR analysis presents only the five best models for each number of predictors based on the value of the R^2. For example, Minitab shows the two regression models include one-predictor models with the highest R^2 values, followed by the two two-predictor models with the highest R2 values, and so on. Thus, 41 models were developed using Minitab 17. "Vars" represents the number of predictor variables included in each model. Predictor variables used in each model are specified by an "***X***." In Minitab, the five best models are shown for each number of predictors except the model that includes all the predictor variables. The best model was selected based on the following criteria:

a) The model should have the highest R^2 and adjusted R^2 among the other models, b) The model should have the smallest MSE, and c) The model should have Mallows' Cp close to the number of predictors in the model including the output variable (constant). It is recommended that the adjusted R^2 over R^2 be used for comparing models with different numbers of terms. Table 5.3 shows the model selected based on the criteria above.

Table 5-3. Selected Best Subsets Model.

Performance Indicators	Value
No. of Predictors	8 (T, P, WS, GS, LP, WT, FL, WM)
R squared	48.70
Adjusted R squared	46.80
Mallows Cp.	8.1
Mean Square Error (MSE)	0.258

Subsequent to the parameter selection step, the following linear regression equation was obtained:

$$\begin{aligned}\mathbf{Productivity} &= 2.17368 + 0.0163662T - 0.0559208P - 0.00772945WS - 0.0106864GS - 0.00810366LP \\ &\quad - 0.0160492WT + 0.0037892\,FL + 0.0792147WM \qquad \boldsymbol{Equation\ 5.1}\end{aligned}$$

5.3.2 Stepwise Regression Modeling

The Stepwise Regression (STR) modeling technique eliminates or preserves predictor variables in order to find a useful subset which should be included in the regression model. Establishing this subset is called the variable selection problem. Two contradictory ideas are behind this step selection approach: a) include every predictor variable that is even slightly connected to the dependent variable in order to get a realistic; and b) complete model and include as few predictor variables as possible because including irrelevant variables will decrease model accuracy. Thus, the aim of variable selection is to attain simplicity and best fit model equilibrium (NCSS, 2018). Three approaches to variable selection are Forward Selection, Backward Selection and Stepwise Selection.

STR analysis was performed using Minitab 17. The first step for developing stepwise in Minitab is to set a significance level (Alpha) for adding or deleting a predictor variable. Alpha-to-Enter and Alpha-to-Remove represent significance levels set to 0.15 by default in Minitab. The significance level (Alpha) effect on performance indicators used to find the optimum Alpha-to-Enter and Alpha-to-Remove values is done by trial and error. Alpha-to-Enter is the value that determines if any of the predictor variables not currently in the model should be added. Alpha-to-Remove is the value that determines if any of the predictor variables in the model should be removed. Figure 5.4 shows that the best statistical performance will be reached when the significance level is set to 0.15.

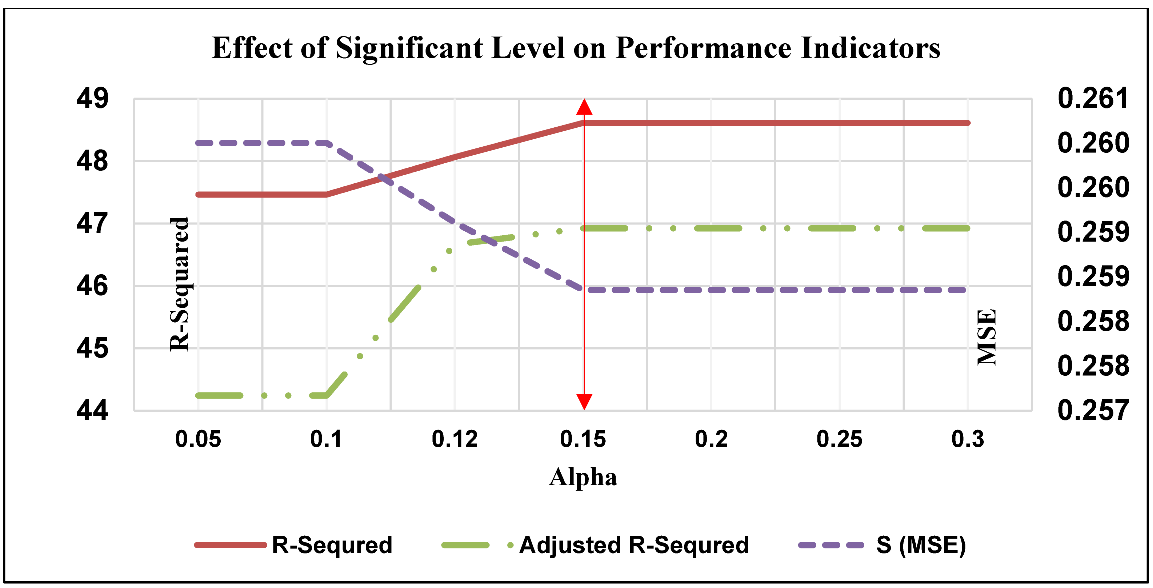


Figure 5-4. Effect of Significance Level on Performance Indicators.

After a significance level is specified, one predictor variable is added to the regression equation only p-value is less than 0.15. In other words, the first predictor should have the smallest p-value among other predictor variables. The next predictor is added only if it has the smallest p-value less than Alpha-to-Enter. After adding the second predicator, the significance level of the first predictor is reassessed if entering the second predicator has an impact on the significance level of the first predictor variable. The first predictor is removed if the significance level of the first predictor is greater than 0.15. A similar step is repeated for adding other predictor variables. It should be noted that the process will stop if no predictor has a *t*-test *P*-value less than 0.15. Subsequent to the predictor variables selection step, the following linear regression model is made (Equation 5.2):

$$\text{Productivity} = 0.312 + 0.507\text{T} - 0.185\text{WT} - 0.106\text{P} - 0.177\text{WS} - 0.113\text{GS} - 0.0848\text{LP} + 0.0497\text{WM} \qquad \textbf{\textit{Equation}}\ \mathbf{5.2}$$

Two variables, humidity and floor level, were removed from the regression equation due to having a p-value greater than 0.15. Table 5.4 shows the statistical performance indicators of the developed model using STR analysis.

Table 5-4. Stepwise Regression Model.

Performance Indicators	Value
No. of Predictors	7 (T, P, WS, GS, LP, WT, WM)
R squared	48.60
Adjusted R squared	46.90
Mean Square Error (MSE)	0.151

5.3.3 Evolutionary Polynomial Regression

EPR is a non-linear regression method classified as a grey box method based on designed model expressions for the given dataset. Figure 5.5 shows the EPR taxonomy in contrast with other modeling techniques. Mathematical modeling can be classified into three groups based on the mathematical structure understanding and the level of prior information required (Giustolisi and Savic, 2006): 1) White box models, where the mathematical structure is transparent, the variables and parameters have physical meaning, and parameters are well identified; 2) Grey box models, which are conceptual models whose mathematical structure is built based on conceptualization or physical insight, but parameter assessment is needed by using data; and 3) Black box models, data-driven or regressive models where the relationship among parameters and variables is unknown and should be estimated. Unlike AI modeling, EPR does not depend on large datasets for model development and EPR provides a model expression for defining the relationship between predictor variables and output. Like other modeling techniques, expert knowledge should accompany the EPR technique so as to validate if the produced mathematical model and correlations between utilized inputs and output are practical.

The EPR was developed by Giustolisi and mainly applied to environmental case modeling (Giustolisi and Savic, 2006; Giustolisi et al., 2008; Doglioni et al., 2008). In a nutshell, the theory behind EPR can be explained as follows: 1) An evolutionary procedure based on Genetic Algorithm (GA) for exploring model structure; and 2) Linear regression step based on least squares (LS) method for calculating model coefficients.

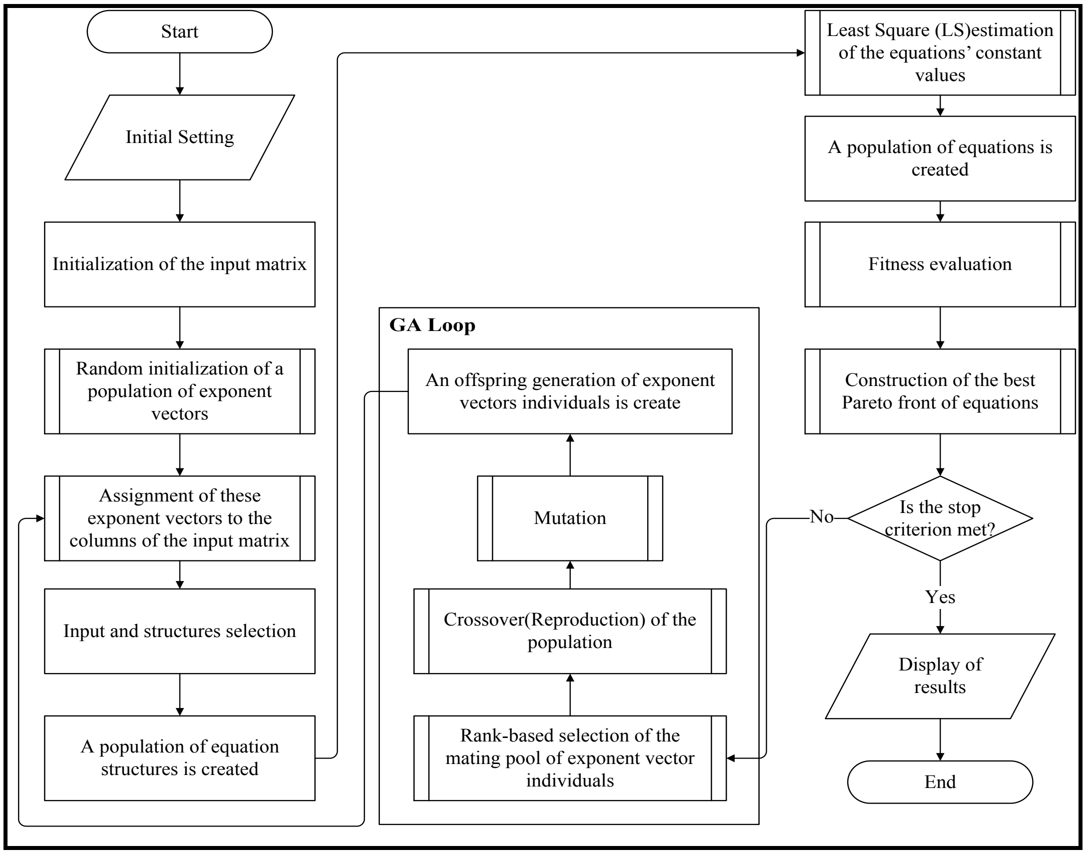


Figure 5-5. EPR Flow Chart (Doglioni et al., 2008).

In the beginning, EPR software was developed in MATLAB environment and later, the software was launched on the Excel platform. Results can be presented in Scatter or Cartesian plot formats. In this research, EPR was able to create several symbolic expressions that can forecast labor productivity based on the given dataset gathered by Khan (2005) for two high-rise buildings. The best expression of labor productivity will be selected based on observed fitness and equation parsimony. Observed data fitness is measured by the value of R^2 and MSE. In addition, the number of terms and factors in each expression should be at a minimum to fulfill the equation parsimony requirement and computational time for generating the best expression (Berardi et al., 2008).

There are seven expression structures available for defining the relationship between input variables and the output variable. Structure selection is contingent upon modeler prior knowledge about the problem that needs to be modeled (Giustolisi and Savic, 2006). Equations 5.3 to 5.9 show the expression structures developed in EPR software:

$$Y = a_0 + \sum_{j=1}^{m} a_j . (X1)^{ES(j,1)} \ldots (Xk)^{ES(j,k)} . f\left((X1)^{ES(j,k+1)}\right) \ldots f\left((Xk)^{ES(j,k+2)}\right) \qquad Equation. 5.3$$

$$Y = a_0 + \sum_{j=1}^{m} a_j \ . f\left((X1)^{ES(j,1)} \ldots (Xk)^{ES(j,k)}\right) \qquad Equation. 5.4$$

$$Y = a_0 + \sum_{j=1}^{m} a_j . (X1)^{ES(j,1)} \ldots (Xk)^{ES(j,k)} . f\left((X1)^{ES(j,k+1)}\right) \ldots (Xk)^{ES(j,k+2)}\right) \qquad Equation. 5.5$$

$$Y = log(a_0 + \sum_{j=1}^{m} a_j \ . f\left((X1)^{ES(j,1)} \ldots (Xk)^{ES(j,k)}\right)) \qquad Equation. 5.6$$

$$Y = exp(a_0 + \sum_{j=1}^{m} a_j \ . f\left((X1)^{ES(j,1)} \ldots (Xk)^{ES(j,k)}\right)) \qquad Equation. 5.7$$

$$Y = sin(a_0 + \sum_{j=1}^{m} a_j \ . f\left((X1)^{ES(j,1)} \ldots (Xk)^{ES(j,k)}\right)) \qquad Equation. 5.8$$

$$Y = tan(a_0 + \sum_{j=1}^{m} a_j \ . f\left((X1)^{ES(j,1)} \ldots (Xk)^{ES(j,k)}\right)) \qquad Equation. 5.9$$

Where, *f*(x) in the first three equations can be selected by adjusting the field "Inner Function" accordingly and can represent no function, logarithm, exponential, tangent hyperbolic, or secant hyperbolic, Xk is the kth explanatory variable, *ES* is the matrix of unknown exponents to be defined by the modeler, a_j is unknown polynomial coefficients, m is the number of polynomial terms, and a_0 is the bias term. When making the symbolic expressions, if EPR cannot find a suitable combination of terms including *f*(x), it discards this function (Giustolisi et al., 2006). The output is rounded off to the closest figure if Modeling Type is selected as the classification; as such, statistical regression modeling should be carefully chosen in situations where the real number is available as a dependent variable. Dynamic regression is available for time series models. The data was normalized prior to the application of EPR software, wherein the inputs and output were set between 0 and 1. EPR software allows the number of terms in every equation in each run to be determined. Exponent nomination should be specified by the modeler, but it should be noted that zero needs to be included in the matrix of exponents to make EPR capable of removing non-influential variables as much as necessary when predicting the output. The nomination value can be positive or negative, wherein the positive and negative values characterize the direct and inverse relationship among predictor variables and their amounts show their importance. The default values for the nomination are -2, -1.5, -1, -0.5, 0, 0.5, 1, 1.5, and 2 (Giustolisi and Savic, 2006). As mentioned above, the GA technique is utilized to identify near optimum model structure. The global search for model structure near optimum is performed by way of standard GA. GA is based on Darwinian evolution and starts with the generation of a set of results known as a population of individual parameters. The parameters being enhanced are coded using “chromosomes.” In typical GAs, binary codes are used to build chromosomes; however, in EPR, an integer coding system is employed to identify candidate exponents’ vector location. EPR uses the following GA parameters (Giustolisi and Savic, 2006): 1) Multiple-point crossover (Spears and De Jong, 1991); 2) Single point mutation; 3) Ranking selection based on the normalized geometric distribution; and 4) Termination criterion as a function of chromosome length, number of polynomial terms *j,* and the number of inputs k in the matrix **X**.

A detailed explanation of a typical GA was presented in Section 3.3.4.1. EPR regression methods can be based on LS method or non-negative LS will generate the expression with only a positive value of a_j unknown as polynomial coefficients. EPR returns several expressions based on model accuracy and parsimony. Model parsimony is implemented by optimizing one of the following options: 1) The number of terms Min (a_j, SSE); 2) The number of independent variables Min (Xi, SSE); or 3) Both strategies: the number of terms and independent variables (a_j,Xi SSE). SSE is the sum of squared estimate of errors. The above-mentioned options can be selected in the optimization strategy scroll down box of the EPR model software. Lastly, training and testing datasets were defined as follows:1) X tab is for defining input; 2) Y tab is for defining the training output; 3) XV tab is for the testing input; and 4) YV tab is for testing output. EPR outcome is presented in five different forms for each model as an Excel file, EPR fitting criteria, Pareto, Symbolic expressions, and Scoter plot. The Excel file includes nine separated tabs as follows: Models, Y_EPR, Graphs, Train_data, Test_data, EPR-Setting, and Y_EPR_test. The following indexes in the “Models” tab were computed using the following equations (Equations 5.10 – 5.14):

$$BIC = \left(1 + d\frac{\log N}{N}\right).SSE \qquad Equation.5.10$$

$$FPE = \left(\frac{1 + d/N}{1 - d/N}\right).SSE \qquad Equation.5.11$$

$$AIC = \left(1 + 2\frac{d}{N}\right).SSE \qquad Equation.5.12$$

$$GCV = \left(\frac{SSE}{(N-d)^\wedge 2}\right) \qquad Equation.5.13$$

$$AVG = 100.\frac{1}{N}\sum_{i=1}^{N}\left(\frac{SSE}{Yi}\right) \qquad Equation.5.14$$

BIC is the Bayesian Information Criterion and the model with the lowest BIC is preferred. The Final Prediction Error (FPE) criterion measures model quality by simulating the situation where the model is tested on a different data set. AIC is the Akaike Information Criterion which estimates the relative information lost by a given model. Thus, the less information a model loses, the higher the quality of that model. Generalized Cross Validation (GCV) estimates the performance of the model based on new data (Liew, 2004). AVG is the Average of the Sum of Squared Errors (SSE) where N is the number of samples and d is the number of independent variables. The Y_EPR and Y_EPR_test tabs display the training and testing set outputs for all generated models.

The generated graph tab shows predicted outputs as well as actual observations. Coefficient of Determination (CoD) and SSE expression and the values are also shown. The next two tabs include the train and test data. The subject of these two tabs is the same as the EPR software file X, Y, XV, and YV tabs. The EPR-Setting tab shows the EPR software tab in the current run of that file. In addition, the Y_rec and Y_V_rec tabs contain data reconstructed by EPR for training and test sets, respectively (Giustolisi et al., 2011). EPR produces a fitting criteria diagram, where the horizontal axis represents the number of terms in each produced expression, while the vertical axis shows the different criteria normalized value (i.e. SSE, BIC, MSE, FPE, AIC, GCV, CoD, and AVG).In each run, for each regression testing and training model, EPR develops numerous scatter plots. The horizontal axis shows the value of predicted productivity, while the vertical axis represents actual productivity (experimental data). At the top of the graph, CoD and AVG are shown as well as the function structure. In addition, a Pareto Graph is developed by EPR, where the horizontal axis demonstrates the 1-CoD value and the vertical one shows the number of considered factors in each model percentage of Xi =(d/N). The Pareto grid shows the developed models as points in the graph. The models that can meet the EPR model selection criteria are shown as a red circle. The number of variables is the minimum and the R^2 (CoD) value is the maximum necessary to meet the requirements for parsimony and model fitness, respectively. Several numbers of symbolic expressions were generated based on the dataset size and level of complexity. EPR produces models for predicting output based on either one or several predictor variables; it can develop Multi Input Single Output (MISO) and/or Single Input Single Output (SISO) models. It is noteworthy to mention that, by using linear interpolation to find missing data points, the model can be developed using an incomplete historical dataset. However, linear interpolation accuracy in reconstructing data points is subject to questions.

5.3.3.1 EPR Optimal Structure

In the early years, EPR methodology was mainly used for hydrological modeling by its developers and more recently, used to model sewer pipe failures and water distribution network deterioration (Giustolisi and Savic 2006, Giustolisi et al. 2007, Doglioni et al. 2008, Berardi et. al. 2008, Rezania et al. 2008, Xu et al. 2011). Thus, EPR capabilities and its outstanding performance in different civil engineering disciplines make it a viable candidate for labor productivity modeling. Since this model has not historically been used for modeling construction labor productivity, software settings need to be set using a trial and error approach. In this model, the EPR setting was changed to identify the optimal setting for datasets available for modeling labor productivity. A specific combination of structure and function was carefully chosen at each setting during the EPR process. The level of EPR model output accuracy at each setting was evaluated based on the fitness function. Table 5.5 shows the different setting results as well as the CoD (or R^2) and the SSE of training dataset values for each setting.

For simplicity, in all the analyses, the number of terms was set to 3 and the range of potential exponents was selected as values between -2 and 2 with a 0.5 incremental step. As mentioned earlier, it is recommended that a zero value be included for discarding those variables not beneficial to the model. EPR analyses with these settings were performed on a personal computer with an i7 dual core 2.6 GHz processor with 8 GB of memory.

Table 5-5. Different EPR Setting Scenarios.

Setting Options	Setting 1	Setting 2	Setting 3	Setting 4	Setting 5
Expression structure	Y=sum(ai*X1*X2*f(X1)*f(X2))+ao	Y=sum(ai*X1*X2*f(X1*X2)))+ao	Y=sum(ai*X1*X2*f(X1*X2)))+ao	Y=sum(ai*X1*X2*f(X1*X2)))+ao	Y=sum(ai*X1*X2*f(X1)*f(X2))+ao
Inner Function	Logarithm	Logarithm	Exponential	Tangent Hyperbolic	Exponential
Modelling Type	STR	STR	STR	STR	STR
Number of Terms	3	3	3	3	3
Optimization Strategy	Min(aj,Xi,SSE)	Min(Xi,SSE)	Min(Xi,SSE)	Min(Xi,SSE)	Min(Xi,SSE)
R2 or CoD	70.34%	72.94%	56.51%	61.07%	77.15%
SSE	0.037	0.034	0.054	0.049	0.029

Table 5.5 shows that Setting 5 produced more accurate results when compared to the other four settings. Of the five settings, Setting 5 had the highest CoD at 77.15% and the lowest SEE, at .029. Thus, Setting 5 became the foundational block for analyzing the effect the EPR models' number of terms has on predicting labor productivity. Accordingly, nine scenarios were planned

based on the EPR models' number of terms. The number of terms increased from one to nine, nine identifying a parsimonious model with an acceptable accuracy based on Setting 5, as well as less computational time.

Figure 5.6 shows model accuracy based on each developed models' number of terms (blue line) and computational times (green line). It can be seen from Figure 5.6. that, generally, increasing the number of EPR terms increases computational time while not necessarily increasing prediction accuracy. It should be noted that the application of these terms also leads to more convoluted relationships for mathematical modeling.

Scenario 4 and 9 show better results than other scenarios. Scenario 4 has a CoD of 78.99% with a computational time of 1140 seconds and Scenario 9 shows an accuracy of 79.29%, with a computational time of 3269 seconds. Although Scenario 9 seems to be a bit more accurate, the computational time and complexity model of Scenario 4 is superior and thus, this scenario was chosen.

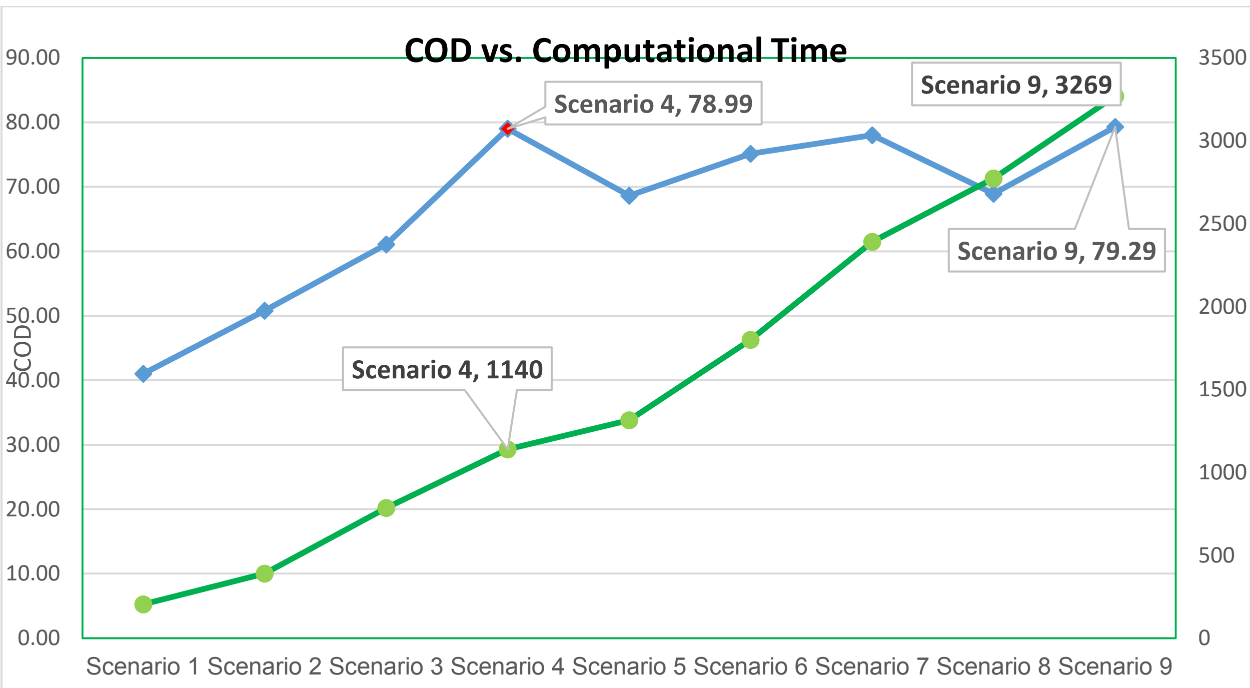


Figure 5-6. Number of Terms, Accuracy, and Computational Time of EPR Models.

5.3.3.2 Modeling Labor Productivity Using EPR

Based on the data of the two high-rise buildings and based on Scenario 4, 17 symbolic expressions were generated to predict construction labor productivity for formwork activity. Table 5.6. shows these expressions along with R-Squared scores. On the right side of the symbolic expression, T, H, P, WT, GS, LP, WS, and FL represents temperature, humidity, precipitation, work type, gang size, labor percentage, wind speed, and floor level, respectively. As discussed earlier, the best model should be selected from all the expressions based on model fitness and parsimony. Model number (no.) 17 was selected as the best one with the highest R-Squared value, even though nine models have acceptable R-Squared scores (Table 5.6). Accuracy indexes such as SSE, BIC, MSE, FPE, AIC, and GCV are shown in Table 5.7. The results in Table 5.7 show that model no. 17 also had the minimum values in all indexes. This observation confirms that this model is the most promising one in predicting the output.

Table 5-6. Symbolic Expressions for Labor Productivity and Related R-Squared.

No.	Symbolic Expression	R^2
1	Productivity = $0.60084T^{0.5}$	35.24
2	Productivity = $-0.12253WT^{0.5} + 0.6659T^{0.5}$	44.77
3	Productivity = $-0.12508WT^{0.5} - 0.15269P^{0.5} + 0.69021T^{0.5}$	48.99
4	Productivity = $-0.13121WT^{0.5} + 0.45488P^{0.5}\ln(P^{0.5}) + 0.69821T^{0.5}$	50.16
5	Productivity = $0.7018T + 1.8681T^2GS\ln(FL^{0.5}/T)$	52.55
6	Productivity = $-0.0053635\ln(WT^{0.5}) + 0.70415T + 2.8636T^2GS^2\ln(FL^{0.5}/T^{0.5})$	62.35
7	Productivity = $-0.0045577\ln(WT^{0.5}) + 0.83771T + 2.6083T^2GS^2\ln(GS^{0.5}FL^{0.5}/T^{0.5})$	65.28
8	Productivity = $-0.0045854\ln(WT^{0.5}) - 0.23854WS^2 + 0.91234T + 2.9959T^2GS^2\ln(GS^{0.5}FL^{0.5}/T^{0.5})$	69.74
9	Productivity = $-0.0054308\ln(WT^{0.5}) - 0.17177WS^2 + 1.1674T^{1.5}+ 5.6197T^2GS^2FL^{0.5}\ln(GS^{0.5}FL^{0.5}/T^{0.5})$	72.72
10	Productivity = $-0.0026134\ln(WTP^{0.5}) - 0.19911WS^2 + 1.0633T^{1.5}+ 5.1662T^2GS^2FL^{0.5}\ln(GS^{0.5}FL^{0.5}/T^{0.5})$	75.19
11	Productivity = $-0.0026134\ln(WT^{0.5}P^{0.5}/ GS^{0.5}) - 0.14358FL^2 + 1.1496T^{1.5}+ 5.5971T^2GS^2FL^{0.5}\ln(GS^{0.5}FL^{0.5}/T^{0.5})$	76.02
12	Productivity = $-0.0037617\ln(WT^{0.5}P^{0.5}/ GS) - 0.19092WS^{0.5}FL^2 + 1.1626T^{1.5}+ 5.7435T^2GS^2FL^{0.5}\ln(GS^{0.5}FL^{0.5}/T^{0.5})$	76.67
13	Productivity = $-0.0031238FL^{0.5}\ln(WTWS^{0.5}P/ GS) - 0.23383FL^2 + 1.1972T^{1.5}+ 5.8289T^2GS^2FL^{0.5}\ln(GS^{0.5}FL^{0.5}/T^{0.5})$	77.66
14	Productivity = $-0.002759T^{0.5}\ln(PWT/ GS^{1.5}) - 0.42887TWS^{0.5}FL^2 + 1.1678T^{1.5}+ 5.7299T^2GS^2FL^{0.5}\ln(GS^{0.5}FL^{0.5}/T^{0.5})$	78.27
15	Productivity = $-0.0021802T^{0.5}\ln(PWT^{1.5}H^{0.5}/ GS^{1.5}) - 0.43625TWS^{0.5}FL^2 + 1.1791T^{1.5}+ 5.7401T^2GS^2FL^{0.5}\ln(GS^{0.5}FL^{0.5}/T^{0.5})$	78.39
16	Productivity = $-0.0021802T^{0.5}\ln(P^{0.5}WT/ GS^{1.5}) - 0.74371THWS^{0.5}FL^2 + 1.281T^{1.5}+ 6.5279T^2GS^2FL^{0.5}\ln(GS^{0.5}FL^{0.5}/T^{0.5})$	78.72
17	Productivity = $-0.0042494H^{0.5}T^{0.5}\ln(P^{0.5}WT/ GS) – 1.0983THWS^{0.5}FL^2 LP^{0.5}+ 1.281T^{1.5}+ 6.1584T^2GS^2FL^{0.5}\ln(GS^{0.5}FL^{0.5}/T^{0.5})$	78.99

Table 5-7. Performance Indexes for Two High-Rise Buildings Downtown Montreal Dataset.

Model:	***SSE***	***BIC***	***MSE***	***FPE***	***AIC***	***GCV***	***AVG***
Model_1	0.0811	0.0835	0.0816	0.0821	0.0820	0.0005	13.9252
Model_2	0.0692	0.0732	0.0700	0.0708	0.0708	0.0004	13.0164
Model_3	0.0639	0.0695	0.0650	0.0661	0.0661	0.0004	12.8015
Model_4	0.0624	0.0679	0.0635	0.0646	0.0646	0.0004	12.7083
Model_5	0.0594	0.0629	0.0601	0.0608	0.0608	0.0003	12.1327
Model_6	0.0472	0.0513	0.0480	0.0488	0.0488	0.0003	11.0896
Model_7	0.0435	0.0473	0.0443	0.0450	0.0450	0.0003	10.5903
Model_8	0.0379	0.0423	0.0388	0.0397	0.0396	0.0002	9.9132
Model_9	0.0342	0.0382	0.0350	0.0358	0.0357	0.0002	9.3314
Model_10	0.0311	0.0347	0.0318	0.0325	0.0325	0.0002	8.9783
Model_11	0.0300	0.0336	0.0307	0.0314	0.0314	0.0002	9.0113
Model_12	0.0292	0.0326	0.0299	0.0306	0.0306	0.0002	9.0154
Model_13	0.0280	0.0313	0.0286	0.0293	0.0293	0.0002	8.7077
Model_14	0.0272	0.0304	0.0279	0.0285	0.0285	0.0002	8.6894
Model_15	0.0271	0.0302	0.0277	0.0283	0.0283	0.0002	8.5980
Model_16	0.0267	0.0298	0.0273	0.0279	0.0279	0.0002	8.7010
Model_17	0.0263	0.0294	0.0269	0.0275	0.0275	0.0002	8.5511

Figure 5.7 on the next page shows the Pareto graph of the symbolic expressions produced based on the dataset. The arrow in the Pareto graph highlights Model no. 17. The horizontal axis shows the value of one minus R^2 and the vertical axis represents the number of considered factors in each model. The normalized dataset was randomly divided into two subsets; namely, as training and testing datasets. A number of 177 (80%) samples were selected for training purposes and 44 samples were considered as the testing dataset. Testing samples were not included in the model during development.

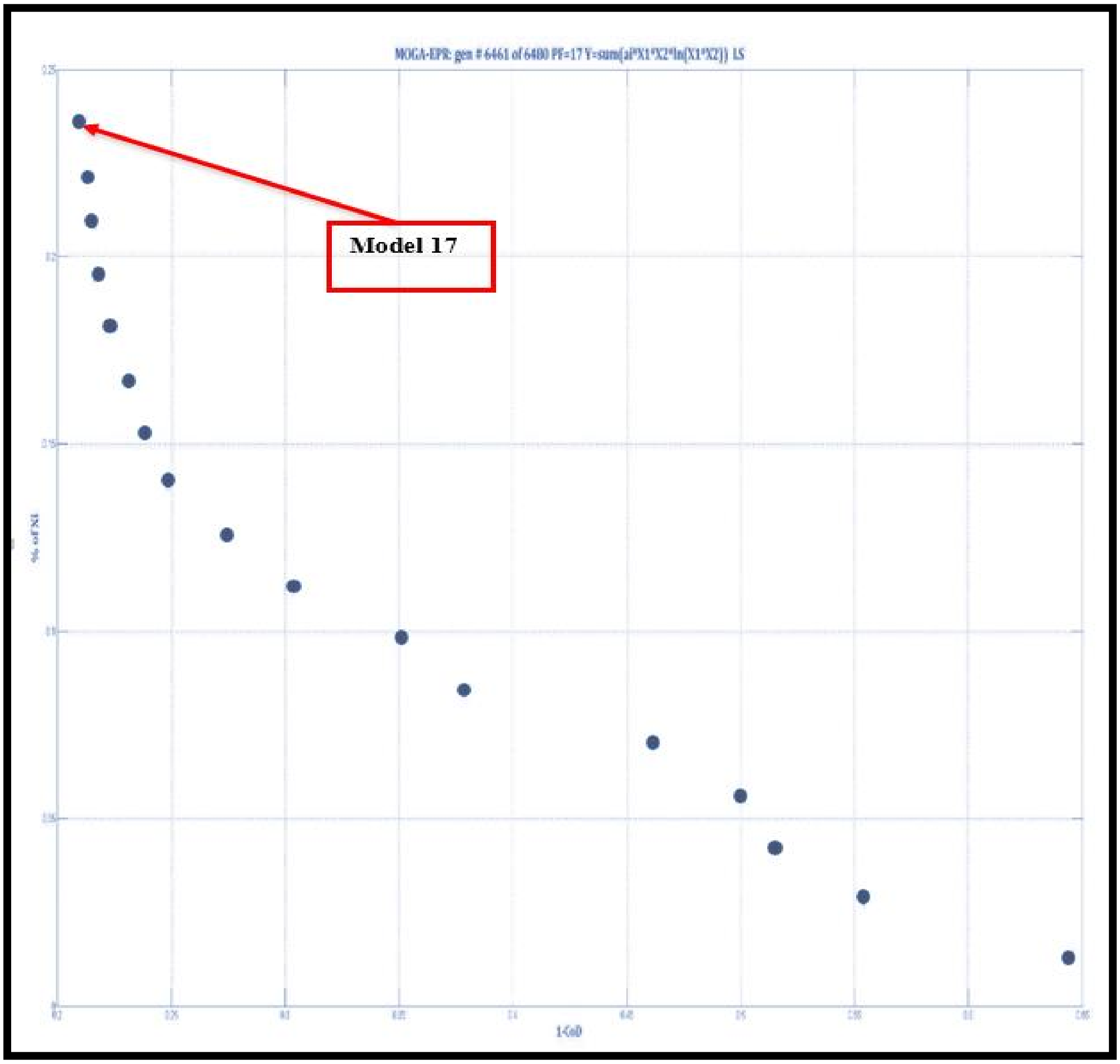


Figure 5-7. Dataset Pareto Model for Two High-Rise Buildings

Figure 5.8 shows actual productivity based on the given dataset and the predicted value using model no. 17, represented by the following mathematical equation (Equation. 5.15):

$$\text{Productivity} = -0.0042494H^{0.5}T^{0.5}\ln\left(P^{0.5}WT/GS\right) - 1.0983THWS^{0.5}FL^{2}LP^{0.5} + 1.281T^{1.5} + 6.1584T^{2}GS^{2}FL^{0.5}\ln\left(GS^{0.5}FL^{0.5}/T^{0.5}\right) \quad \text{Equation. 5.15}$$

The blue line shows actual productivity values against the EPR predicted productivity values (red line) using Equation 5.15. An acceptable prediction pattern was attained between the experimentally gathered values and the EPR predicted values.

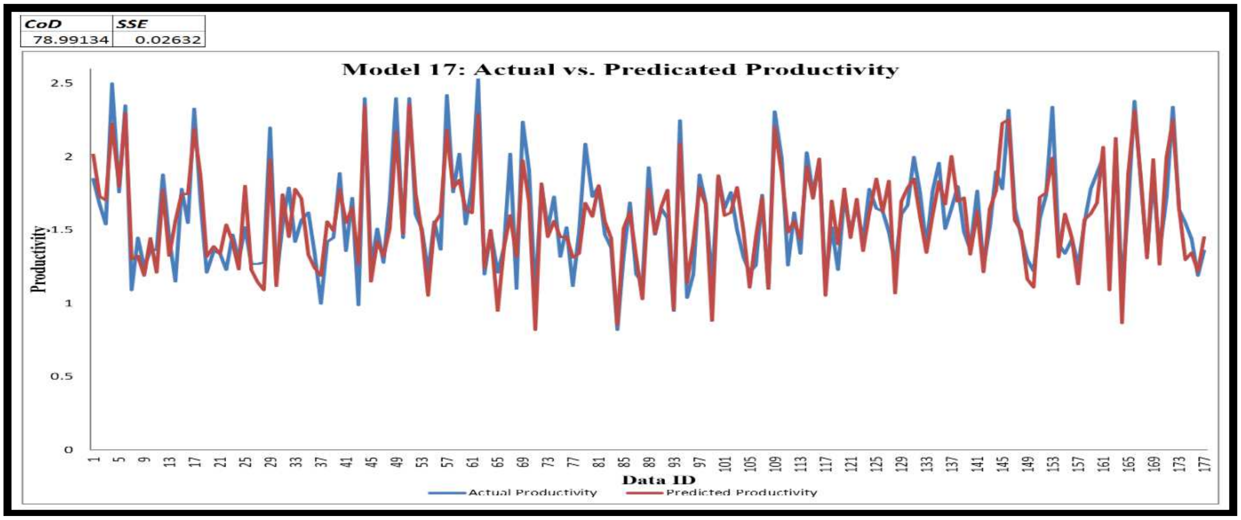


Figure 5-8. Actual vs. Predicted Productivity for Training Dataset Using Model No. 17.

After the training, the trained EPR model performance was validated using the testing dataset not utilized as a part of the model development process. The purpose of this step was to study the trained model's aptitudes so as to generalize training to situations that have not appeared throughout the training step. In order to validate the trained EPR models' capability over the testing dataset, Equation 5.15 was used to predict labor productivity curves with the results shown in Figure 5.9.

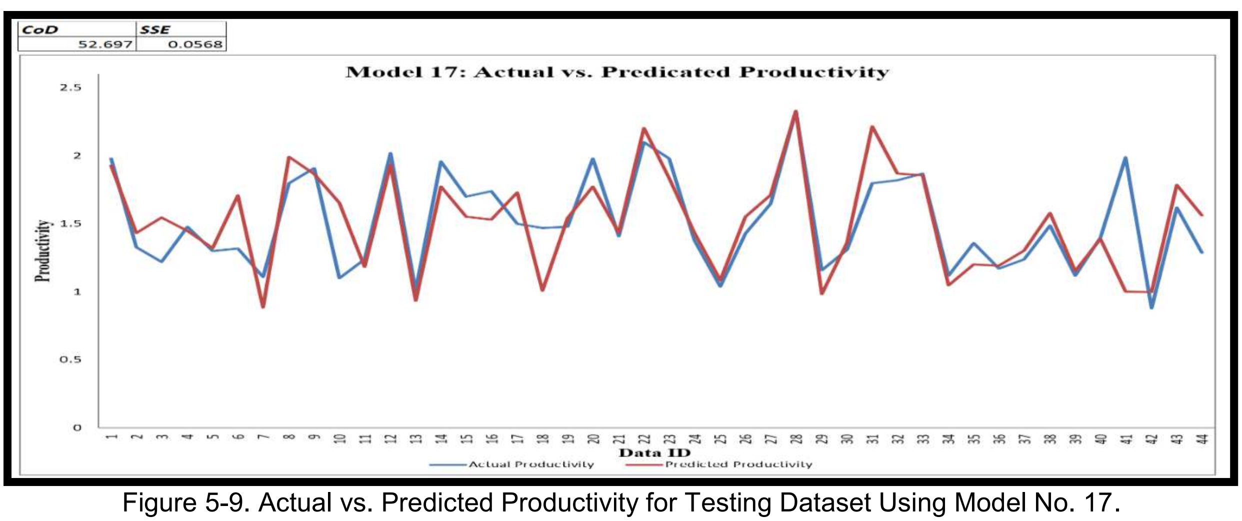


Figure 5-9. Actual vs. Predicted Productivity for Testing Dataset Using Model No. 17.

Figure 5.9 shows that when using the testing dataset, the predicting model does not show a strong prediction pattern between actual data and the EPR developed predicted data. It should be noted that the EPR process requires some subjective judgment based on the analyst's experience instead of being purely based on mathematical criteria (Rezania et al., 2008). In this research, EPR was used for the first time for labor productivity modeling. It is possible that some subjective judgments will lead to improved EPR results. More experimentation is needed from other researchers using EPR for productivity modeling. Because EPR shows better performance than the two other regression techniques, a sensitivity analysis was performed in the next section.

5.4 EPR Sensitivity Analysis

A sensitivity analysis was performed to identify the variables' effect on predicted productivity. The factor value under analysis was changed while the rest of the variables maintained the initial value. Figure 5.10 and Table 5.8 show the effect of changing all productivity input variables. In this figure, the vertical axis represents productivity value and the horizontal axis shows normalized variables' value. Since each variable has its own unit, the horizontal axis was plotted by means of normalized value from 0.01 to 1. This graph was made for two purposes as follows: a) To understand the interdependencies between productivity and its input variables; and b) To identify the most sensitive independent variables. For a better picture of each variable effect, each variable actual values were tabulated below normalized values. The results show a strong relationship between temperature and gang size as inputs and labor productivity as the output. The effect of temperature on productivity has been well documented (Abele, 1986; Thomas and Yiakoumis, 1987; Moselhi,1997; Moselhi, 2005; Lee, 2007). Meanwhile, gang size trends show overmanning issues; increasing the number of workers within the same trade can lead to productivity loss. Although it is possible that gang size can increase rates of production by eliminating overtime problems such as fatigue, it is possible that it will lower productivity due to congestion and less direct supervision.

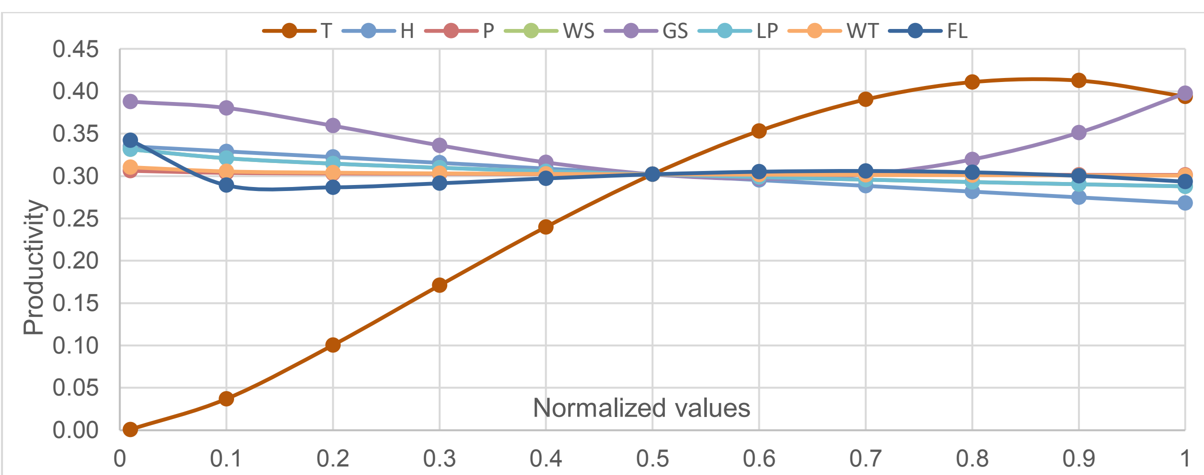


Figure 5-10. EPR Sensitivity Analysis for a Two High rise Buildings Dataset.

It should be noted that there is an improvement in productivity at the last 30% of the variation in gang size but the amount of improvement is not substantial when compared to gang size. A detailed discussion of overmanning can be found in Chapter 2.

Table 5-8. Actual values of the parameters.

Parameter	Actual values of the parameters										
T (C)	-25.5	-20.9	-15.8	-10.7	-5.55	-1	4.65	9.75	14.85	19.95	25.05
H	18.79	25.9	33.8	41.7	49.6	57.5	65.4	73.3	81.2	89.1	97
P	0.03	0.3	0.6	0.9	1.2	1.5	1.8	2.1	2.4	2.7	3
WS	3	7	11	15	19	23	27	31	35	39	43
GS	8	10	11	13	14	16	18	19	21	22	24
LP	29	31	33	34	36	38	40	42	43	45	47
WT	1	1	1	2	2	2	2	2	3	3	3
FL	1	3	4	6	7	9	11	12	14	15	17
WM	1.01	1.1	1.2	1.3	1.4	1.5	1.6	1.7	1.8	1.9	2

Floor level trends are shown in Figure 5.12 and Table 5.8 exhibit interesting behavior as well. There is an obvious inverse relation between floor level and productivity for the first 50% of the variation in floor level, which can be caused by the learning curve factor. As Khan (2005) has mentioned, the floor level variable is the only variable which synchronizes with project start. Therefore, it is the only variable that can gradually incorporate the effects of learning. Productivity shows improvements after workers pass the learning curve phase. Humidity and labor percentage trends are very similar and have an inverse relation with productivity, i.e. an increase in humidity or labor percentage causes a decrease in productivity. Low humidity percentages have a positive impact on productivity; however, passing beyond a certain humidity level will impact labor productivity negatively. Labor percentage can contribute to labor productivity negatively if the ratio of labors to the skilled workers is higher than the norms of the industry for a task.

In other words, there should be a specified optimal labor percentage in the crew for supporting skilled work otherwise overall productivity is adversely impacted. For example, in a hydropower dam under construction in Northeast Canada, the optimum labor percentage value for formwork activities was estimated between 25 to 30% of a crew. Any more or less than this was proven to impact formwork productivity negatively. Despite the overall changes in productivity trends in this sensitivity analysis, changes in work type and precipitation values show an inverse relationship; this change can be ignored due to low change amounts.

5.5 Regression Modeling Techniques Comparison

Having applied the different regression techniques on the given dataset and quantified their basic performance indicators, it is beneficial to recapitulate the results and present some performance assessments. In this research, the application of each three techniques explained previously was performed and tested against the datasets of two high-rise buildings related to formwork operation. A summary of the best achieved results for each of the three techniques is presented in Table 5.9.

Table 5-9. Performance Results Comparison.

Technique	R-Squared	MSE	Time (Sec)	Number of Variables
BSR	0.468	0.258	~2	8
STR	0.486	0.258	~2	7
EPR	0.523 (test)	0.057	1140	8

From this comparison, the following remarks can be concluded: 1) EPR regression produces higher accuracy and lower MSE than BSR and STR; 2) BSR and STR techniques have shown very close performance regarding R-squared and MSE; 3) EPR has the highest computational time as compared to the two other techniques because EPR datasets were divided into training and testing datasets for modeling. However, whole datasets were applied on BSR and STR. The number of variables used in the productivity model is very close, seven to eight variables; 4) Since none of the regression techniques achieved high accuracy, it is surmised that abovementioned techniques are not suitable for the given datasets; and 5) It is possible that data preprocessing and studying the behavior of the given datasets before applying these techniques may result in more accurate models.

5.6 Artificial Intelligence (AI) Approach

AI has provided more powerful tools for the construction industry over the past decades. Several AI molding techniques have been employed in the construction industry such as expert systems (ES) and NN. A considerable part of construction industry problems is in the form of analogy-based problems such as last-minute bids, design under pressure, etc. Thus, NN techniques as compared to other conventional practices are more appropriate in modeling construction industry problems that demand analogy-based resolutions (Moselhi et al., 1991a). There are four major steps for modeling analogy-based problems using NN: i) Gathering historical data, ii) Building and configuring the relevant network, iii) Initializing weights and biases; and iv) Training and validation step. In this research, four types of NN were applied for modeling labor productivity. These were Back Propagation, RBF, GRNN, and ANFIS. In addition, a novel NN with unique features was proposed for achieving a model with higher accuracy for predicting labor productivity. A detailed explanation of all the modeling techniques used, along with the proposed model, will be discussed in the following sections.

5.6.1 NN Productivity Modeling Using Backpropagation

In this section, ANN was applied to model labor productivity. NN is mostly used for unknown function approximation. As described in the literature review, a key ANN feature is its learning ability. It can be trained by historical datasets to find the accurate relation between inputs and outputs as well as predicting the output(s) for new inputs. In this research, ANN models were developed, trained, validated, and tested in MATLAB 2017a with 221 data points. The dataset was randomly divided into 80 and 20% groups, used for training and testing results, respectively. Several ANN models were developed, different in three aspects: number of neurons in a hidden layer which varies between five and 100, random groups of datasets, and the number of hidden layers varying between one and two. A Bayesian Regularization (BR) algorithm was used for data training. BR is commonly used in noisy and small problems. The algorithms attempted to minimize the sum of the squared errors by updating the network's bias and weight. Training sets were used to adjust the network structure based on the associated errors until the best structure was reached. Validation sets were utilized to measure network generalization capabilities and to pause training when generalization stopped improvement. After training, testing sets provided an independent network performance index. For each ANN model, trials were performed to reach the lowest error. Model performance was assessed based on R-squared and MSE developed through MATLAB coding according to the following equations, where "t_i" is the target value while "o_i" is the output value:

$$R^2 = 1 - \frac{\sum_i (t_i - o_i)^2}{\sum_i \left(t_i - \frac{1}{n}\sum_i t_i\right)^2} \qquad Equation.\,5.16$$

$$MSE = \frac{1}{n}\sum_i (t_i - o_i)^2 \qquad Equation.\,5.17$$

The CoD (R-squared) is often used in statistical analysis since it is easy to calculate and understand. It fluctuates among [0, 1] and evaluates the percentage of total differences between estimated and target values with respect to the average. Several ANN with the different number of neurons and hidden layers were developed to find the best model for identifying labor productivity. The number of hidden layers varied between one and two and models were trained by five, ten … 100 neurons. Considering the differences in the number of the neuron and hidden layer, 32 different models were developed, and their results compared. Figures 5.11 and 5.12 display the effect of the number of neurons on the CoD for one and two hidden layers. As can be seen in Figure 5.11, the R^2 are mostly between 90-100% for the training phase and 70-90% for the testing phase. The model with one hidden layer and 50 neurons shows maximum accuracy. For two hidden layers models, the model with 20 neurons in each layer showed the best performance in predicting labor productivity. Increasing the number of hidden layers resulted in better performance but this takes more computational time and does not change model accuracy in any significant way. In this research, the maximum number of neurons that could be considered in the ANN model was 60 due to extreme computational time and insignificant improvement to model accuracy. MSE value was the smallest in the models with two hidden layers and 20 neurons and one hidden layer and 50 neurons (Figures 5.13 & 5.14). Model performances were assessed based on R^2 and MSE, as summarized in the following Figures.

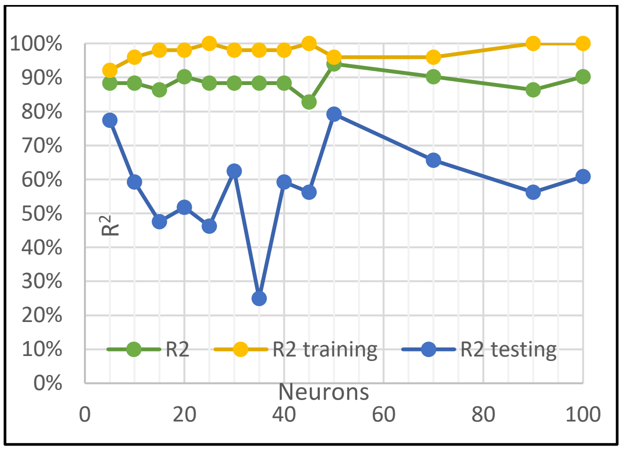


Figure 5-11. R^2 values of ANN models using BP algorithm with 1 HL.

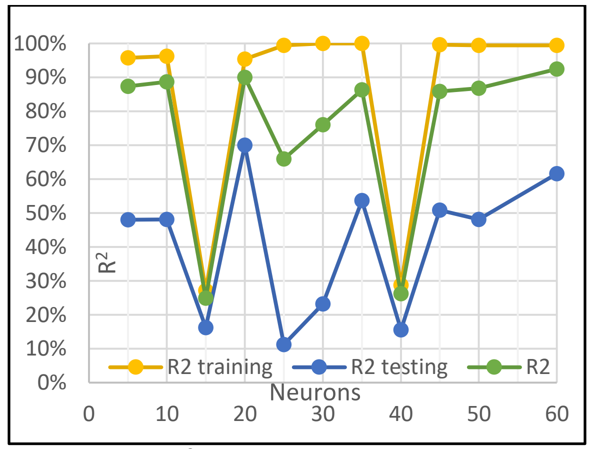


Figure 5-12. R^2 values of ANN models using BP algorithm with 2 HL.

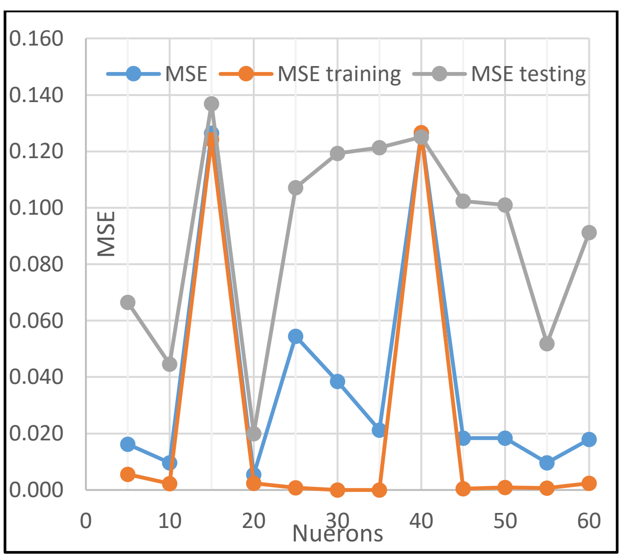


Figure 5-13. MSE Values of ANN Models with Respect to Number of Neurons 1HL.

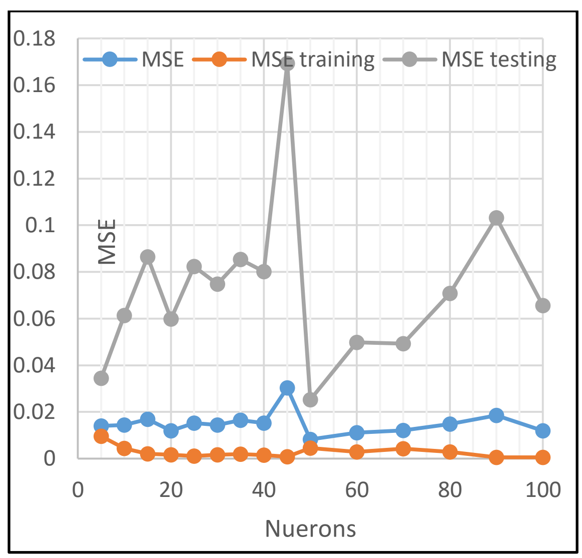


Figure 5-14. MSE Values of ANN Models with Respect to Number of Neurons 2HL.

It should be mentioned that no performance index was available during the validation phase while the given datasets were trained by the BR algorithm because the algorithm does not validate data and the datasets were randomly divided only into trained and test datasets. As can be seen from the model comparisons in Table 5.10 and Table 5.11, the final model was the one with two hidden layers and 20 neurons, which showed the acceptable accuracy for identifying labor productivity with lowest computational time. The model has MSE and R^2 performance value indices of 0.023 and 0.900, respectively. Therefore, this model was considered for comparison with the ANIFS model in the next sections.

Table 5-10. Performance Indices for Models with One Hidden Layer.

Neurons	5	10	15	20	25	30	35	40	45	50	70	90	100
MSE	0.014	0.014	0.017	0.012	0.015	0.014	0.017	0.015	0.030	0.008	0.012	0.019	0.012
MSE train	0.010	0.004	0.002	0.002	0.001	0.002	0.002	0.002	0.001	0.005	0.004	0.001	0.001
MSE test	0.03	0.06	0.08	0.06	0.08	0.07	0.08	0.08	0.06	0.024	0.04	0.10	0.06
R^2	0.88	0.88	0.86	0.90	0.88	0.88	0.88	0.88	0.82	0.94	0.90	0.86	0.90
R^2 train	0.92	0.96	0.98	0.98	1	0.98	0.98	0.98	1	0.96	0.96	1	1
R^2 test	0.77	0.59	0.47	0.51	0.46	0.62	0.25	0.59	0.56	0.79	0.65	0.56	0.61

Table 5-11. Performance Indices for Models with Two Hidden Layers.

Neurons	5	10	15	20	25	30	35	40	45	50	60
MSE	0.0162	0.0096	0.1264	0.0215	0.0545	0.0384	0.0212	0.1264	0.0183	0.0184	0.0096
MSE train	0.0055	0.0022	0.1242	0.0200	0.0008	0.0000	0.0000	0.1267	0.0005	0.0008	0.0007
MSE test	0.0665	0.0446	0.1369	0.0230	0.1071	0.1193	0.1213	0.1251	0.1024	0.1010	0.0518
R^2	0.874	0.887	0.249	0.900	0.660	0.760	0.863	0.262	0.859	0.868	0.925
R^2 train	0.958	0.962	0.272	0.954	0.994	1	1	0.288	0.996	0.994	0.994
R^2 test	0.480	0.481	0.162	0.700	0.112	0.232	0.537	0.156	0.509	0.481	0.616

The error histogram of the final model with two hidden layers and 20 neurons is presented in Figure 5.15. It can be seen from the bars that most of the errors oscillate between -0.55 and 0.75 in all the training and testing phases. The concentration of errors was 0.003, which is a small error for prediction. The R^2 value was 95.41% in training dataset, which shows that the outputs are very close to target values. The R^2 value for testing was 70%, proof that the model is able to predict 70% of future outcomes accurately.

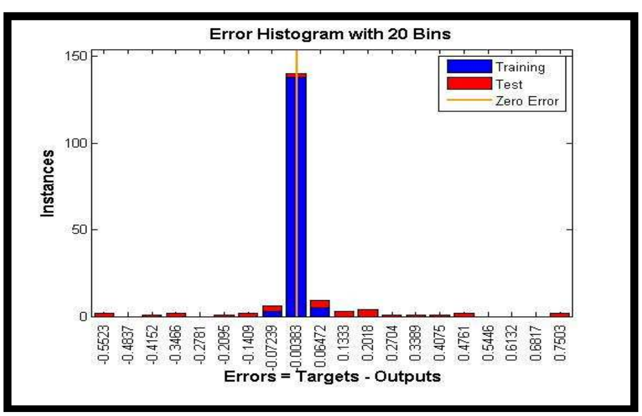


Figure 5-15. Error Histogram for final model.

5.6.2 General Regression Neural Network (GRNN)

GRNN, first proposed by Donald F. Specht in 1990, is often used for nonlinear function approximation. It has a special linear and radial basis layer which makes it different from radial basis networks. GRNN is a NN model that mimics nonlinear relations between a target variable and a set of predictor variables. GRNN falls into the class of probabilistic NNs and requires less training samples in comparison to a backpropagation NN. The GRNN main advantage is that since available datasets for developing NNs are not usually sufficient, probabilistic NNs will be more attractive for modeling. In other words, GRNN can solve any function approximation problems in case insufficient data is available in abbreviated time. In GRNN, the target value of the predictor is achieved by considering the weighted average of the values of its neighboring points. The target variable distance of neighbors plays a key role in predicting target value. Neighboring points close to target points have a greater impact on target value; distant points, on the other hand, are not influential as much as close neighbor points. The radius base function is used for calculating the level of influence of neighboring points (MathWorks, 2018). As mentioned, GRNN is able to build a model with a relatively small dataset and has the capability to handle outliers (Yip et al., 2014). There are two main disadvantages associated with GRNN relative to other techniques; it needs considerable calculation to evaluate new points and it is not able to ignore unrelated inputs itself and needs major algorithm modifications. Consequently, this method is not a choice for problems with a substantial number of predictor variables. The GRNN algorithm can be enhanced by advancing GRNN in two of the following ways (Specht, 1991): 1) Using clustering versions of GRNN; and 2) Using parallel calculations to take advantage of GRNN structure characteristic. In addition to the abovementioned drawbacks, GRNN models can be large due to having one neuron for each training row. For developing the GRNN model, DTREG was utilized; thus, after the model was constructed, DTREG provided an option for facilitating the removal of unnecessary neurons from the model. By removing unnecessary neurons, the computational time is reduced, and it becomes possible to improve model accuracy (DETRG, 2018). DTREG was utilized, along with three criteria available for guiding the removal of neurons, in order to select the best possible model: 1) Minimize error. Removing neurons as long as removing a neuron will cause the model error to increase the above minimum found; 2) Minimize the number of neurons. Removing neurons will stop until the model error goes beyond model error with all the neurons; and 30 limit the number of neurons to a certain number. Removing neurons until the number of neurons set by the user is met. Some other features of the DTREG GRNN model are as follows:

1) Single sigma for the whole model: This is the simplest and fastest model type as it relies on a single sigma value for all points. Sigma is a value for determining the radial base function spread; 2) Sigma for each variable: This option will calculate the sigma value for each predictor variable in the model; 3) Sigma for each variable and class: This option calculates the sigma for each predictor variable and for each target category; and 4) Kernel function type: The kernel is a similarity function and controls how the influence of a point declines as the radius from the point increases. DTREG provides two types of kernel functions: 1) Gaussian: A Gaussian function causes the influence of a point to decline according to the value (height) of a Gaussian distribution centered on the point. The equation of the Gaussian function is:

$$f(x) = \frac{1}{\sqrt{2\pi\sigma}} e^{\left(\frac{-x^2}{2\sigma^2}\right)} \qquad \text{Equation 5.18}$$

2) Reciprocal: The influence of the point decreases as a linear function of the distance from the point. The developed GRNN model accuracy was compared against other models' by using the same dataset. Eighty percent of the dataset was selected randomly as the training set, which corresponded to 177 input-output pairs. Twenty percent of the data was kept unused for testing, which corresponded to 44 input-output pairs. Note that all techniques used for modeling labor productivity in this study used the same training and testing dataset for a proper comparison approach. In addition, the Gaussian kernel function type was selected as it is the best function among other kernel functions and a single sigma for the whole model was selected to reduce computational time. Using a trial and error approach to select the best model, three models were developed based on three options provided by the software: remove unnecessary neurons, minimize error, and the constant number of neurons. Table 5.12 summarizes various statistical indices for the developed models.

Table 5-12. Performances Indices for GRNN.

Performance index	# of Neuron	R2 Train	R2 Test	MSE Train	MSE Test	RMSE Train	RMSE Test	MAE Train	MAE Test
Minimize error	107	0.877	0.647	0.0148	0.0675	0.1218	0.2599	0.0791	0.168
Minimize number of neurons	34	0.758	58.70	0.017	0.071	0.131	0.267	0.098	0.178
Number of neurons	10	0.648	0.511	0.042	0.082	0.206	0.286	0.147	0.216

The best GRNN model was found to have 107 nodes with an R^2 value of 54.73%, which is higher than the two other approaches. Other information extracted from the selected model was as follows: 1) Optimal value of Sigma = 0.7154881 and 2) Analysis run time: 01:07.24.

5.6.3 Adaptive Neuro-Fuzzy Inference System (ANFIS)

ANFIS is used in various engineering fields such as environmental engineering, civil engineering, electrical engineering, etc. (Ying and Pan, 2008; Subasi et al., 2009, Alashary et al., 2009). ANFIS utilizes a hybrid learning algorithm which can model the relationship between predictor variables and respond variables based on expert knowledge by using NN capabilities; it represents expert knowledge in the form of fuzzy if-then rules with the approximation of membership functions from given predictors and response datasets. Fuzzy logic handles the vagueness and uncertainty associated with the system being modeled whereas the NN provides model adaptability. By combining the learning abilities of a NN with the reasoning capacities of fuzzy logic into a unified platform, ANFIS can be considered as an enhanced predication tool in comparison with a single methodology one. ANFIS can adjust MF parameters and linguistic rules directly from NN training capabilities with respect to refining model performance.

ANFIS is able to capture expert knowledge regarding a nonlinear system and its behavior in a qualitative model without quantitative descriptions of the system. Fuzzy Interference System (FIS) is a knowledge interpretation technique based on the concept of fuzzy set theory, fuzzy “IF-THEN” rules, and fuzzy reasoning, where each fuzzy rule characterizes a state of the system. ANFIS TOOLBOX (Figure 5.16) uses a Sugeno FIS for a structured approach to generate fuzzy rules by using a given dataset (Negnevitsky, 2005).

To develop labor productivity using the ANFIS TOOLBOX, the following steps were taken:

1) Load data for training and testing phases from file or workspace. Training and testing data are matrices with ten columns where the first nine columns contain data for each FIS predictor variable and the last column contains the response data. It should be noted that the same 177 data points were used for training and the other 44 for testing purposes;

2) Generate FIS model structure by choosing the subtractive clustering technique. Subtractive clustering technique is faster than grid partitioning and with the satisfactory result for justifying use. Thus, subtractive clustering was selected, and its parameters are presented in Figure 5.17. Based on the selected parameters of subtractive clustering, 63 clusters were detected as the most suitable MF number. It should be noted that the number of clusters and MFs are equal;

3) Select one of two ANFIS TOOLBOX methods provided for training the MF. These include BP and the hybrid method. In this research, the hybrid method was selected because it generates better results than backpropagation. The hybrid method includes backpropagation and least squares for MF parameter estimation, backpropagation for estimating input MF parameters, and least square for output MF parameters; and

4) Set training epochs and tolerance, which work as the stop criteria for training. The training process will be terminated if one of these conditions is met.

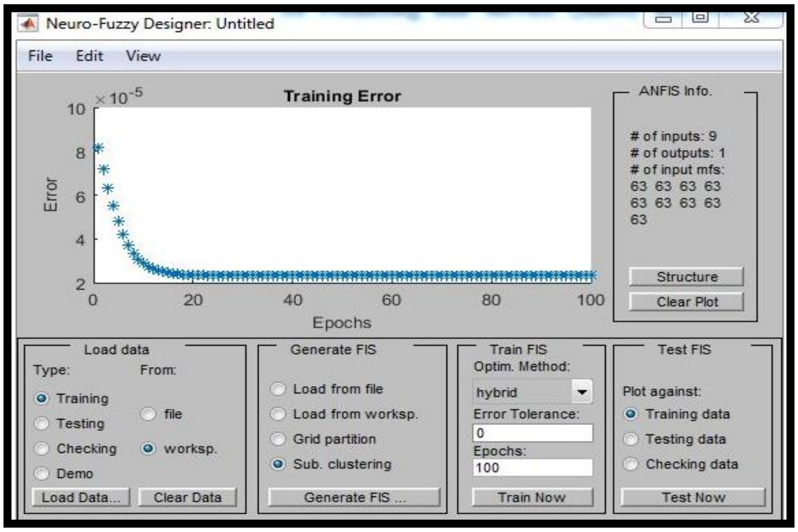


Figure 5-16. GUI of ANFIS in MATLAB 2017a.

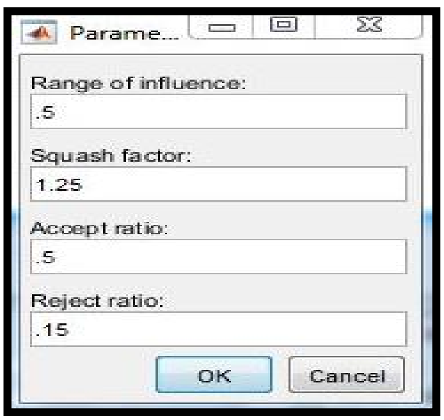


Figure 5-17. Subtractive Clustering Parameters.

ANFIS parameters were selected to reach higher accuracy with less computational time. Table 5.13 shows the selected model parameters.

Table 5-13. ANFIS Parameters for Modeling Labor Productivity.

ANFIS Parameters	
Number of Input Variables	9
Training Data Points	177
Testing Data Points	44
Number of Layers	5
Operator	Subtractive
Number of Membership Functions (MF)	63
MF Type	Bell shape
Transfer Function of Output Layer	Linear
Training Algorithm	Hybrid
Error Tolerance	0
Number of Epochs	100

The model reaches a training MSE of 0.00024 after 100 epochs. Figure 5.18 show the predicted daily productivity against corresponding actual values.

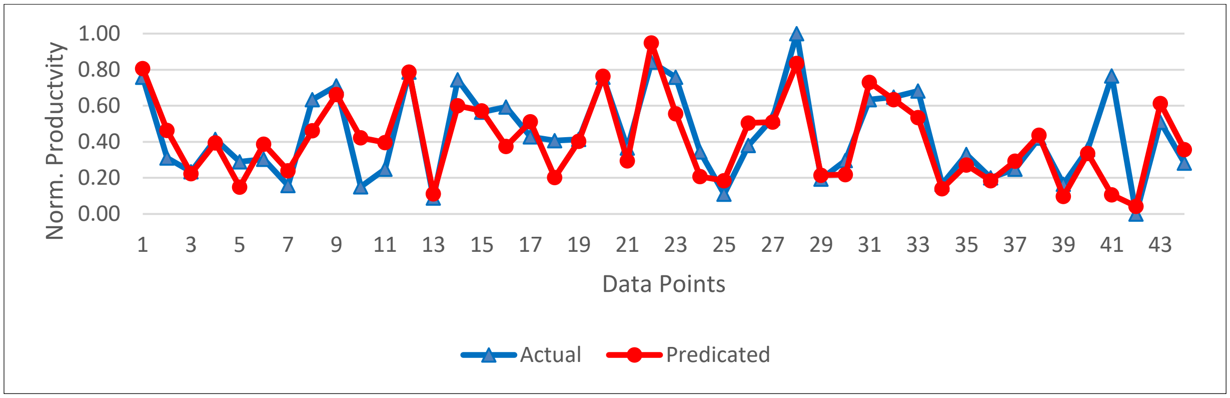


Figure 5-18. Actual vs. Predicate Value Using ANFIS.

Table 5.14 summarizes the dataset various statistical indices using the developed ANFIS model.

Table 5-14. Statistical Indicators of Developed ANFIS Model.

R	0.81
R-Squared Train	0.89
R-Squared Test	0.66
MSE Train	0.01
MSE Test	0.02
MAE Train	0.017
MAE Test	0.097
RMSE Train	0.114
RMSE Test	0.146

5.7 Proposed PSO-RBFNN for Modeling Productivity

In this section, an overview of used machine learning algorithms in the proposed model is presented. In the previous studies, different machine learning techniques employed for modeling productivity, all of which have their pros and cons. For instance, linear regression algorithm usually takes pairs of inputs and labels and tries to fit a function in such a way that the difference between the data pairs and all the points on the function is minimized. Although this technique is easy to implement, it only looks at linear relationships between dependent and independent variables. In addition, the discussed methods are highly dependent on the quality of the dataset, and those models cannot be used for all the challenges associated with unbalanced datasets. There is a need to propose a robust productivity model which is able to fit the given dataset behavior and proposes enough generalizability. Since in the construction datasets, there is much nonlinearity involved, NN prediction outperforms algorithms such as linear regression. This is mainly because NN can leverage between subtle changes in data and structural components. Technically, NN consists of interrelated neurons placed over different layers, which generates output(s) for a given input(s) fed to the network. To be able to extract components that have shown critical effects in the process of prediction, NN maps the input data from raw Euclidean space to some interrelated representation space known as layers. This effect can be approximated via a loss function which NN tries to minimize. Loss function functionality biases the weights towards minimized loss. NN generally consists of three main layers: input, hidden, and output. Learning how to map the input layer to the output layer is called training and is accomplished by the hidden layer. NN can be categorized concerning its architecture, number of epochs, minibatch, loss function, momentum, batch-normalization, weight-normalization, etc. Epochs are the feeding cardinality of each input sample to the network, and minibatch is referred to the breakdown size of each training sample. Momentum is the regularization scheme for better controlling the weights of the network. Batch-normalization is the process of normalizing each minibatch using a normal distribution. Weight-normalization is the process of normalizing the weight vectors to reduce the discrepancies among all the weight values. Choosing a proper network architecture with special settings is challenging and completely dependent on input type and task, either classification or regression. Utilizing a NN with simple architecture is desirable rather than having a convoluted multilayer neural network. The simplicity of NN architecture will lead to less computational time and application flexibility. Thus, RBFNN is selected to model labor productivity. RBFNN is a powerful artificial neural network that has been applied with success to many engineering areas due to advantages associated with its algorithm. RBFNN was selected as the basis for this developed model due to the following advantages:

1. RBF is a kind of NN, and its main difference with regular NN is representing the given input data as a statistical distribution (mainly Gaussian) and continuing the process of training with parameters of the chosen distribution;
2. Less computational time (both in training and in test) as compared to other techniques due to its simple topological structure (Jain et al., 2011). RBFNN structure simplicity can be considered its main advantage over ANN. As explained in the ANN section, the numbers of neurons in each hidden layer, as well as the number of hidden layers, play a significant role in model accuracy. However, increasing the number of neurons and hidden layers will increase both model complexity and computational time;
3. From the generalization point of view, RBFNN can respond well to patterns which are not used for training. This is a significant advantage over the ANFIS modeling technique. In RBFNN, the rules can be defined based on the functions that adapt themselves to the test dataset variability. In other words, the generated rules are as flexible as needed to

cover all the possible system states being modeled. Overall, in NN regression using RBF, functions are better than ANFIS since RBFNN follows the behavior of the test dataset in a curve shape manner; and

4. RBFNN shows resilient noise tolerance for the given data, which improves the permanency of the developed model. This is an advantage over ANN, ANFIS, and GRNN. The presence of noise in a dataset is a pervasive problem that may lead to model failure. Here, noise and outliers are used interchangeably; however, there is a slight difference between these two concepts. Noise can be as a result of a mistake in a dataset, but outlier data is “an observation which deviates so much from the other observations as to arouse suspicions that it was generated by a different mechanism” (Hawkins, 1980).

Modifying RBFNN’s algorithm and including a pre-processing phase for any given dataset led to a robust model with higher performance for predicting labor productivity. Figure 5.19 shows the workflow of the proposed PSO-RBNN.

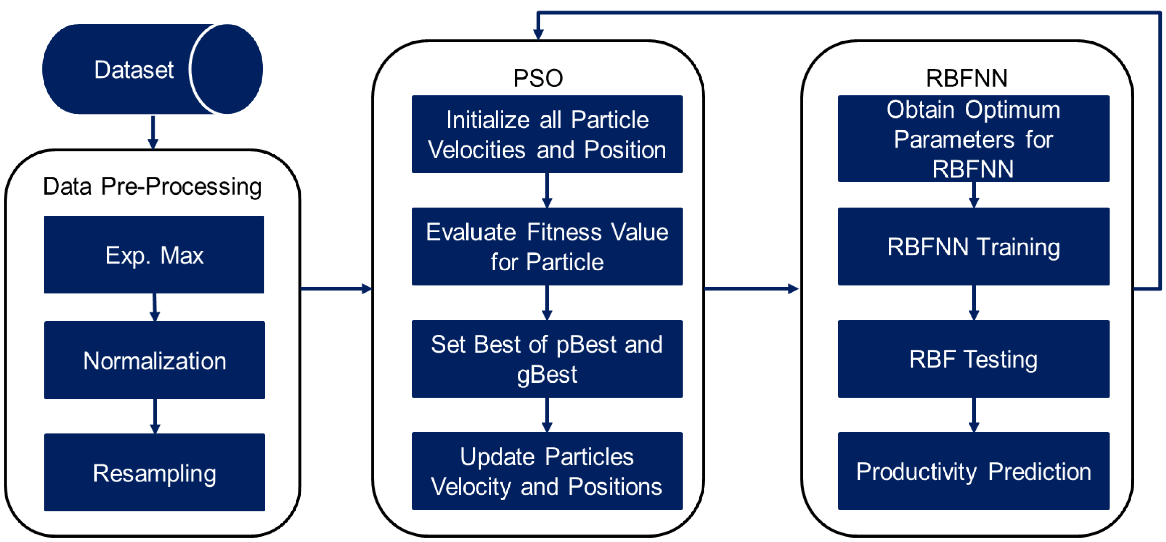


Figure 5-19. PSO-RBFNN Diagram for Predicating Labor Productivity.

5.7.1 Data Preprocessing

In this research, an effort was made to model the nine predictor variables’ convoluted relations and target based on actual datasets gathered from two high-rise buildings using RBFNN. The RBFNN model was trained using the backpropagation algorithm to minimize MSE with nine predictor variables (temperature, humidity, precipitation, wind speed, gang size, labor percentage, work type, floor level, and work method) and the desired output (productivity).

To prepare the input data for the proposed model, a series of data preprocessing operations are conducted. Normalization operation is applied to the prepared dataset to exclude distortions in the data. Expectation-Maximization is to replace the missing variable parameters and also to consider the latent variables in the input data. Moreover, resampling operation is employed to augment the prepared dataset and increase the generalizability of the trained model.

5.7.1.1 Expected Maximization

Expectation maximization (EM) is a method that uses consecutive guesses to approximate the maximum likelihood function. The EM algorithm is a way to obtain maximum likelihood estimates for model parameters when data is partial, has missing data points, or has overlooked latent variables. Two processes were included in each EM iteration as follows (Gupta and Yihua, 2011):

1. E-step. In this step, the missing data were assessed given the dataset and current estimate of model parameters (Equation 5.19):

$$x^{(m)} = \arg\ \max_{x \in X(y)} p\left(x \middle| y, \theta^{(m)}\right) \qquad \text{Equation 5.19}$$

2. M-step. In this step, the likelihood function was maximized under the hypothesis that the missing data is known. The missing quantified data from the previous step was used as a replacement for the actual missing data (Equation 5.19 to 5.20):

$$\theta^{(m+1)} = \arg\ \max_{\theta \in \Omega} p\left(x^{(m)} \middle| \theta\right) \qquad \text{Equation 5.20}$$

Table 5.15 summaries the notation for Equation 5.19 and 5.20.

Table 5-15. Notation Summary.

X	Support of *X* (closure of the set of x where p(x|θ) > 0)
p(y |θ)	Density of y given θ; also written as p(Y = y |θ)
X(y)	Support of X conditioned on y (closure of the set of x where p(x| y,θ) > 0)
θ(m)∈Ω	m^{th} estimate of θ
x	Complete data
y	Given observation
θ ∈ Ω	Parameter(s) to estimate, Ω is the parameter space

The abovementioned steps are repeated until stability is reached. In this research, EM was used because EM is the process of leveraging low-frequency values, which have a more significant share in the data balance distribution in the proposed model. It is essential to keep the data distribution around its mean since it is likely to guarantee the stability of the generated model.

5.7.1.2 Normalization

Normalization is the process of quantizing input data into a bounded interval (e.g. [0,1]) with respect to a distribution (usually normal distribution). Normalization is a method for suppressing high frequency (HF) data. HF data usually contains distortions, which can lead to system weakening. In addition, the NN technique modeling values should be in the same range to avoid having an ill-conditioned model. Normalization can ensure stable convergence of weight and biases NN models. Normalization can be applied to different types and sorts of models. The process of normalizing data in this model followed a Gaussian distribution with specific values for mean and variance. One common normalization method is to apply normal distribution with mean and variance equal to zero and one, respectively. For most of the given dataset, this approach worked well. However, herein, a normal-like distribution with a threshold on its parameters (mean and variance) was applied (Equation 5.21). These values were computed by applying expectation-maximization on the given dataset and by attempting to minimize the following function (Roweis and Zoubin, 2001):

$$z = \frac{x - \mu}{\sigma} \qquad \text{Equation 5.21}$$

Equation 5.22 minimizes the weighted difference between the approximated function f times its occurrence probability for a small bias value equal to μ. By minimizing this function, the stability criteria for each zone was computed to increase the sensitivity of this value to the locality axiom mentioned before. The following formula (Equation 5.23) also minimizes the valid value for perturbation. In other words, the dataset is being forced to be abiding by a specific tolerance. This is useful since it can provide a robust variance around μ.

$$\min_{\mu} \| f(x + \mu) p(x + \mu) - f(x) p(x) \| \qquad \text{Equation 5.22}$$

$$\min_{\sigma} \| x - \sigma \| + \sigma(1 - p(x)) \qquad \text{Equation 5.23}$$

5.7.1.3 Resampling of Dataset

One of the practical ways to improve NN model resiliency against unknown data is by resampling the dataset. It is essential to mention that resampling has nothing to do directly with the trained model and is categorized as a preprocessing step before training. Resampling can be categorized as the following (Oppenheim, 2005): 1) Upsampling: The up-sampling approach is to increase the sampling rate by an integer factor. For example, upsampling by factor 2 means to fill in the missing value between two consecutive data points using interpolation (Figure 5.21). In simple terms, upsampling is the dataset augmentation process using the locality principle. As can be seen from Figure 5.20, the data dimensions are augmented by a coefficient which usually is an integer. This coefficient refers to the scale of the augmentation, and if the coefficient is 2, it means that the data will be augmented in double and the empty generated space will be filled by average local values. Upsampling can be done in many different formats like bilinear or bi-cubic; and 2) Downsampling: The down-sampling approach is to decrease the data sampling rate by an integer factor. For example, downsampling by factor 2 means to preserve only every second sample (Figure 5.21). The down-sampling process is the reverse of the up-sampling procedure and shrinks the input data by a coefficient factor. Assuming the coefficient factor is 2 in the down-sampling process, the dimension of the data will be minimized to half. Similar to up-sampling, downsampling can be executed in different ways like loss removal, bilinear, etc.

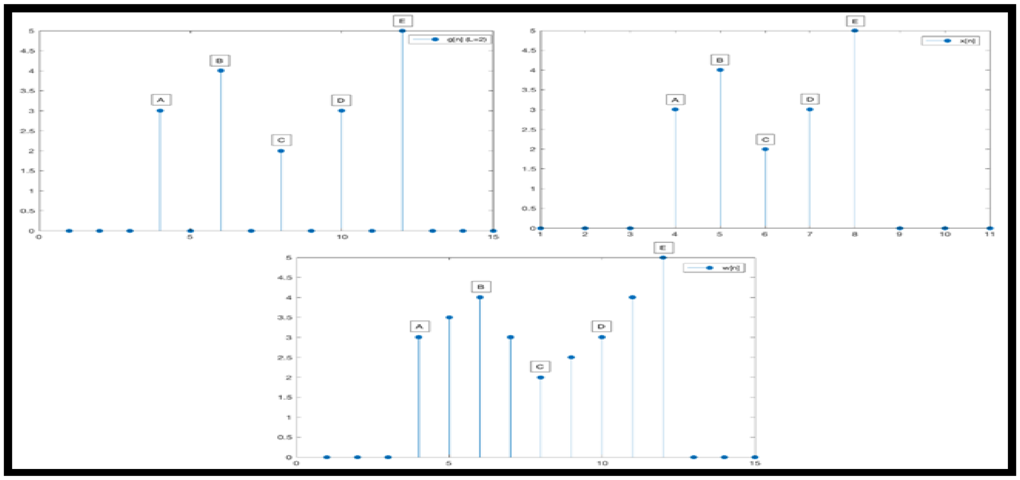


Figure 5-20. Up sampling by Factor 2

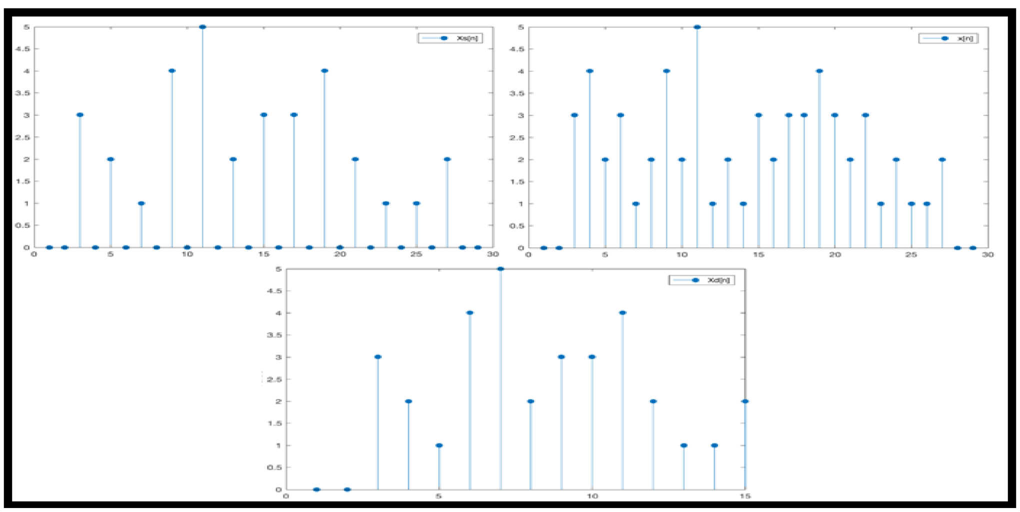


Figure 5-21. Downsampling by Factor 2

Both upsampling and downsampling have their pros and cons and based on the task in which they have been deployed, can be effectual. In this research, upsampling was used because the dataset size is quite small and needs to be augmented. Since the data type of the proposed model is just raw numbers, and unlike images, there is no strong dependency, and up-sampling can be applied to any coefficient value as needed (no more than 20). The main reason for using downsampling is to reduce data noise, especially when the distribution of the features or columns in the dataset is not uniform. It should be noted that upsampling and downsampling were implemented based on the distribution behavior of the normalization phase. In other words, the smaller the data, the more the sample will be extended.

5.7.2 Radial Basis Function Neural Network (RBFNN)

In this research, a feed-forward RBFNN with one hidden radial basis layer is employed (Moody and Darken, 1989). Given a proper number of units, RBFNN can determine any multivariate continuous function on a compact domain to an arbitrary accuracy (Park and Sandberg, 1991). RBFNN is very capable of approximation of nonlinear dataset. It also fits better and has higher prediction accuracy for noise-free data. In case of noisy data, RBFNN's fitting and prediction error are minor, and the convergence rate is faster in comparison to other neural networks such as BP. The topology can improve the learning speed and avoid the local minimum at the same time. The related transfer function adopts radial basis functions especially the Gaussian function. Since Gaussian is simple, not much complexity would be added if there is a multivariable input. It is also easy to be analyzed theoretically. RBFNN is very fast self-learner and has self-organizing, and self-adaptive capability. RBFNN is able to achieve a wide range of data fusion and data parallel processing at high speed. In following the details of RBFNN is explained thoroughly. The RBFNN architecture is composed of three layers: input, hidden, and output. The hidden layer includes nodes which use radial basis function (RBF), denoted φ(r), as the activation function for nonlinearity. The nonlinear transform of the input variables is performed by the hidden layer, and output layer maps the transformed variables into a new space. In other words, the output layer is linear and provides a summation at the output units. Generally, all RBF nodes have the same nonlinearity $(\vec{x})$ =$(\vec{x}-\vec{c}i)$, i=1, 2,…,n where $\vec{c}i$ is the prototype or center of the ith node and $\varphi(\vec{x})$ is an RBF. Also, a bias neuron is added in the hidden layer with a constant activation function $\varphi 0(r)$=1. (Wu et al., 2012). Figure 5.22 shows the architecture of RFBNN.

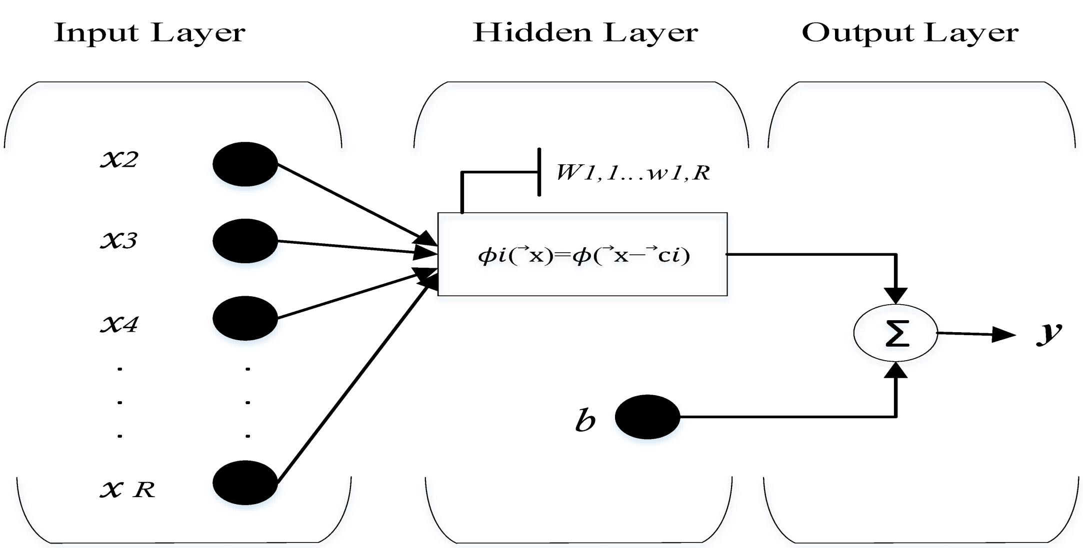


Figure 5-22. Architecture of RFBNN.

For input $\vec{p}$, the output of the RBF network is given by Equation 5.24:

$$y(\vec{x}) = \sum_{k=1}^{n} w_k \varphi(\|x_j - c_i\| \,, \qquad i = 1,2 \dots, n \qquad Equation\ 5.24$$

Where ($\vec{x}$) is the ith output, w_k is the connection weight from the kth hidden unit to the ith output unit, and $\|x_j - c_i\|$ denotes the Euclidean norm. The RBF activation function has various form. However, the Gaussian function is typically selected, and such an RBF network is usually termed the Gaussian RBF network.

Therefore, the net input to the radial basis function is the vector distance between its weight vector ***w*** and the input vector ***x***, multiplied by the bias b (the ‖dist‖ box in this figure accepts the input vector p and the single row input weight matrix and produces the dot product of the two). Usually, the Gaussian function is used as RBF and regularized by a center and width and the Euclidean distance between the input vector x_j and the radial basis functional center is calculated by Equation 5.25:

$$\varphi(x_j - c_i) = \exp\left(-\frac{1}{2\sigma_i^2} \|x_j - c_i\|^2\right) \qquad i = 1,2,\dots,m \qquad Equation\ 5.25$$

In this function, $\|x_j - c_i\|$ is Euclidean norm; x_j is the jth input vector; c_j is the center of ith basis function with the same dimension of x_j; σ_i is the ith neuron radial basis function width parameter; i is the number of hidden layer nodes; j =1, 2, . . . , m; j is the number of input vectors; and J is the total number of input vectors. In the proposed architecture, a Gaussian function is used as the activation function. So, the linear function output is shown in Equation 5.26.

$$y(\vec{x}) = \sum_{i=1}^{k} w_i \exp\left(-\frac{1}{2\sigma_i^2} \|x_j - c_i\|^2\right) \qquad Equation\ 5.26$$

Where w_i is the connection weight between the hidden layer and output; O_i is the output value of the i th node. Thus, it can be seen that the center c_i, width parameter σ_i, and the connection weight w_{il} are very important parameters that affect the accuracy of prediction. In the training process of the RBFNN, for each neuron's weighted input, the distance between the input vector and the relative weight vector is calculated. The RBFNN configuration is presented as a minimization goal function. The variables to consider are the number of hidden layer nodes, the center locations c_i, width σ_i, and the connection weights w_i. In this research, particle swarm optimization (PSO) algorithm is employed as a training method to search for the optimum parameters c_i, σ_i, and w_{ij} that minimize the difference between real and predicted matrices of the productivity parameters. After each iteration, the network's error is determined, and if the error goal is not met, the next neuron is added, and this operation is iterated until the error goal is achieved, or the maximum number of neurons is reached.

5.7.3 Particle Swarm Optimization Algorithm (PSO)

The particle swarm optimization (PSO) was inspired by birds' behavior and developed by Kennedy and Eberhart (1995). PSO operates as an evolutionary algorithm that generates a random population of probable solutions, which are called particles. The particles movement direction over the available search space is directed by the best-recognized positions of each particle, p_{best}, and the global best position found during the movement of the swarm, g_{best} (Kennedy and Eberhart, 1995). The position of each particle i in the search space introduces values of the optimization problem variables. The objective function, F, of the optimization problem is evaluated for the position of each particle in the search space. The best-known positions of each particle, $p_{\text{best}i}$, is the position that gives the best value of the objective function and the particle position that has the best evaluation of the objective function in the population is the global best position, $g$best. Technically, PSO uses a swarm of particles or feasible solutions which move over the available solution space to find the optimum solutions. In this study, PSO provides the final analysis of the hyperparameters of RBFNN (Perng et al., 2014). Figure 5.23 shows the flowchart of the optimization process of RBFNN with PSO and the steps are explained as follows:

Step 1: Initialize the population with N particles and all particles velocities and positions.

Step 2: Evaluate fitness value for each particle.

Step 3: If the current fitness is not greater than previous pBest then the fitness value should be evaluated again for each particle.

Step 4: If the current fitness is greater than previous pBest then set best of pBest and gbest.

Step 5: Update Particles velocity and position

Step 6: If criterion is not met or maximum iteration is not reached, then go to Step 2.

Step 7: Stop if criterion is met or maximum iteration is reached.

Step 8: Obtain the optimum parameters of the RBFNN.

For each dimension of the search space, the particle's velocity depends on the positions of the best-known solutions, $p_{\text{best}i}$ and g_{best}, and the current position. For each iteration, n, the velocity in each dimension is calculated by using Equation 5.27 (Lee and El-Sharkawi, 2008):

$$V_{id}^{n+1} = wV_{id}^{n} + c_1 r_1 (P_{id}^{n} - X_{id}^{n}) + c_2 r_2 (P_{id}^{n} - X_{id}^{n}) \qquad Equation\ 5.27$$

Where d = 1, 2. . . D; i = 1, 2. . . N, where N is the size of the swarm; r_1 and r_2 are a random number uniformly distributed in [0, 1]; c_1 and c_2 are positive constant parameters called acceleration coefficients. It has been found that when c_1= 2 and c_2= 2, the velocities provide particle movement that improves overall procedure effectiveness; $X^n{}_{id}$ is the position of particle "i" in the past iteration; $V^n{}_{id}$ is the velocity in the past iteration; ω is inertia weight that controls the impact of previous velocities and is usually considered to be equal to 1; and n = 1, 2, 3,…, determines the iteration number.

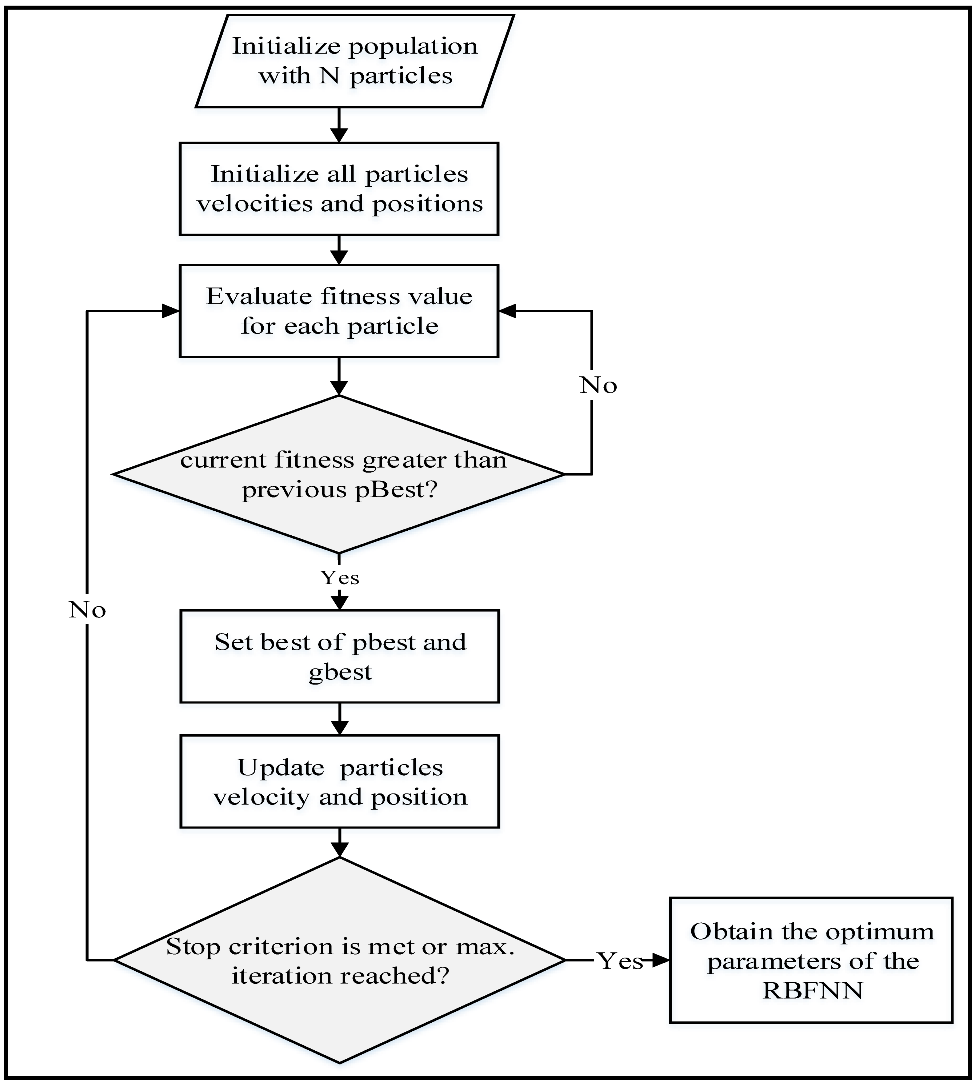


Figure 5-23. The flowchart of the optimization process of RFBNN with PSO.

Moreover, the new position is calculated as using Equation 5.28 (Park and Sandberg, 1991):

$$X_{id}^{n+1} = X_{id}^{n} + V_{id}^{n+1} \qquad Equation\ 5.28$$

Where X_{id}^{n+1} and V_{id}^{n+1} are position and velocity in the current iteration, respectively. When the particle moves to the new position, the objective function evaluates iteratively. The process continues until the maximum number of iterations is reached, or the convergence criterion of the objective function is fulfilled. The position which optimizes the value of the objective function of the problem is achieved by the movement of the particles through the search space. In this research, the objective function which determines the RBFNN performance is represented by MSE (Equation 5.29):

$$MSE = \frac{1}{m}\sum_{i=1}^{n}\left(k_i - \hat{k}_i\right)^2 \qquad Equation\ 5.29$$

Where k_i and $\hat{k}_i$ are actual and predicted normalized permeability coefficient vectors, respectively, and m is the total number of data sets.

5.8 Model Evaluation and Implementation

There is no standard approach to calculate the number of nodes in the hidden layer. Therefore, trial and error approach is started with minimum number of nodes in hidden layer to train the network. The training process must terminate if the training is performed many times, does not reach the specified training duration or the network does not converge to a predetermined accuracy. As a consequence, the number of hidden nodes should be added gradually. The training process continues until a satisfactory result is reached. As a result of this approach, the number of hidden nodes is determined as 47. Considering the numbers of input and output neurons as 9 and 1, the PSO-RBFNN architecture is 9-47-1.

The proposed PSO-RFBNN is implemented on a prepared dataset and evaluated with a real-world case study. The swarm population size is set to 45, and each particle in the algorithm represents the variables of c_i, σ_i, and w_{ij}. In the first step, the input data is modified by the introduced preprocessing operations. The input data space span is limited from 0 to 1, and RBF center c_i is constrained in the range of [0, 1]. Based on the conducted experiments, the width σ_i are considered in the range of [1, 45], and the connection weights w_{ij} are constrained in the range of [0, 100]. As mentioned in the previous section, regarding the defined range of parameters, particle swarm is initialized randomly.

Then PSO start processing based on each step of the flowchart presented in Figure 5.23. The maximum iteration number is defined as 100 iterations and mean squared error less than or equal to 0.0001 is defined as the stop criterion. In addition, the PSO parameters are set up to: ωmax = 0.99, ωmin = 0.4, $x$min = -10, $x$max = 10, and Vmax = 20. The PSO-RBFNN processes used to build the standalone software was done using MATLAB.

It should be noted to avoid the local minima problem, ring topology is utilized. Ring topology means that each particle is influenced only by particles in its own neighborhood. Each section of the software will be discussed in detail in the following section. The comparative results of proposed PSO-RFBNN model and regular RBFNN on the test data set are presented in Table 5.16.

Table 5-16. Comparative Performance Indicators of RBFNN and PSO-RBFN.

Model	R	R^2	MSE	RMSE	MAE
RBFNN - Train	0.905	0.811	0.015	0.103	0.081
RBFNN - Test	0.818	0.673	0.045	0.213	0.151
PSO RBFNN - Train	0.985	0.969	0.004	0.064	0.036
PSO RBFNN - Test	**0.944**	**0.891**	**0.019**	**0.116**	**0.139**

Figures 5.24 and 5.25 shows the predicted daily productivity against corresponding actual values for train and testing datasets.

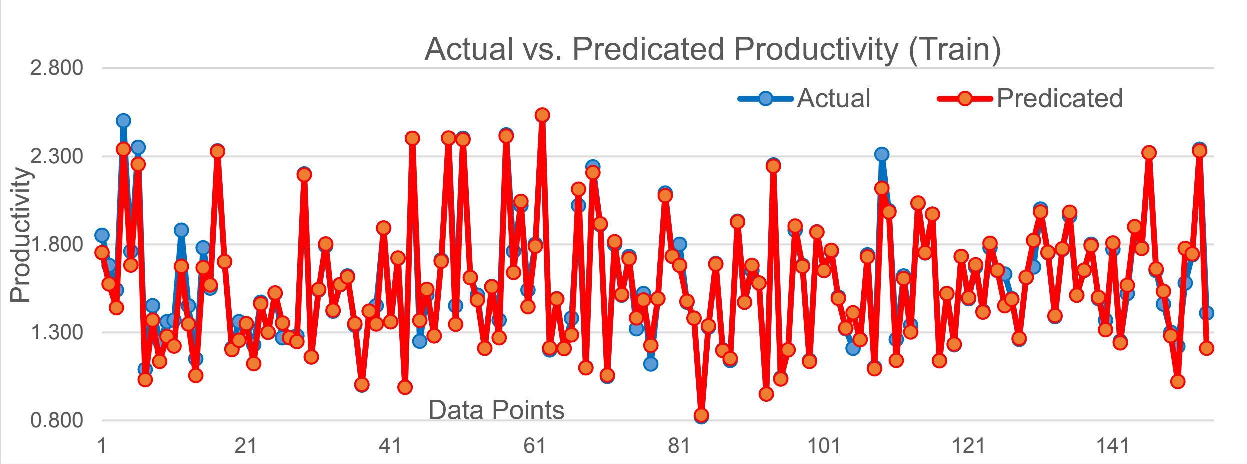


Figure 5-24. Actual vs. Predicted Values for Training Dataset.

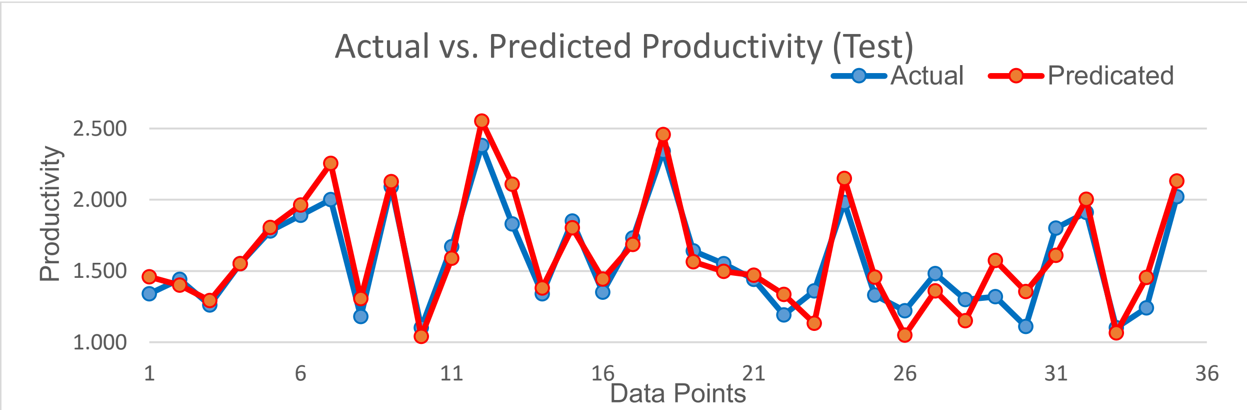


Figure 5-25. Actual vs. Predicted Values for Testing Dataset.

PSO algorithm is utilized for determining RBF neural network parameters, c_i, σ_i, and w_{ij}. This algorithm compares the MSE of different networks and it chooses the neural network with minimum MSE. Results show that PSO algorithm can be used as an alternative way in selecting network.

5.8 AI Modeling Techniques Comparison

After having applied the different AI techniques and the developed PSO-RBFNN on the given dataset and quantified their statistical performance indicators, the results were analyzed, and their performance was assessed. In this research, the application of each of the five techniques described previously was achieved and tested against Khan's datasets retrieved from two high-rise buildings related to formwork operation. The performance of PSO-RBFNN is compared with ANN, GRNN, ANFIS, and RBF. The results are shown in Figures 5.26 and 5.27 and the details of comparison are recorded in Table 5.17.

Table 5.17 shows that the proposed PSO-RBFNN has less testing MSE and a more compact structure than the other algorithms. Moreover, the testing time and the training time of the PSO-RBFNN are least than that of the other algorithms. The results of PSO-RBFNN further show that the PSO algorithm is more suitable to optimize RBFNN to achieve better results than the other algorithms. The proposed PSO-RBFNN is a more suitable and effective method than the other neural networks for predicting labor productivity with the given dataset.

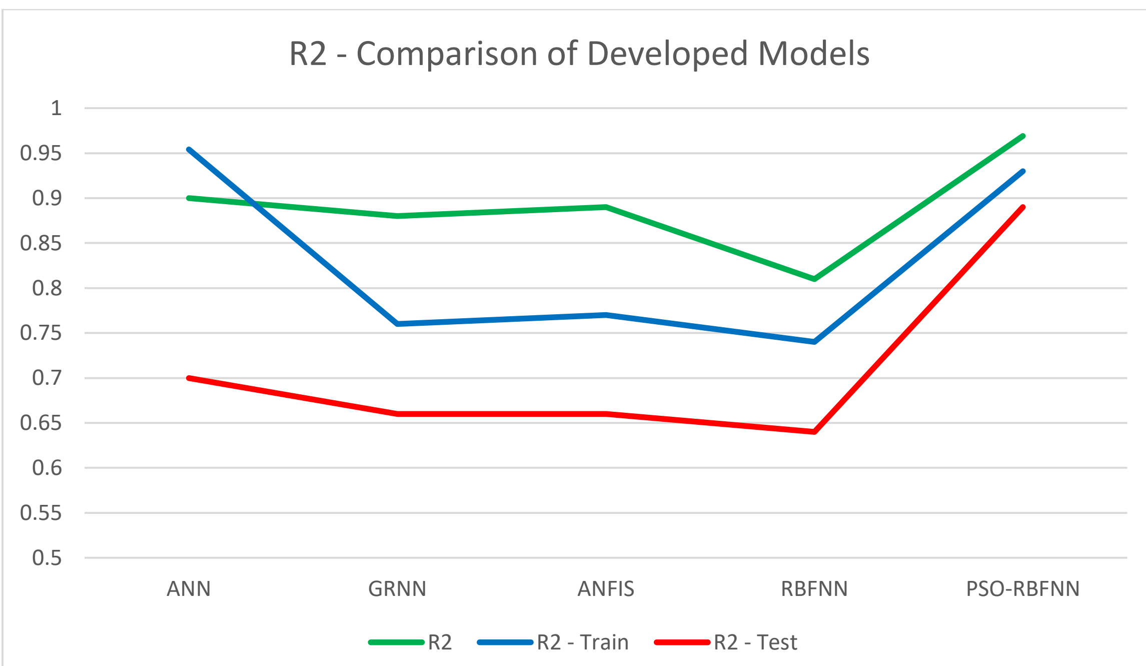


Figure 5-26. Comparison R^2 for Different Algorithms

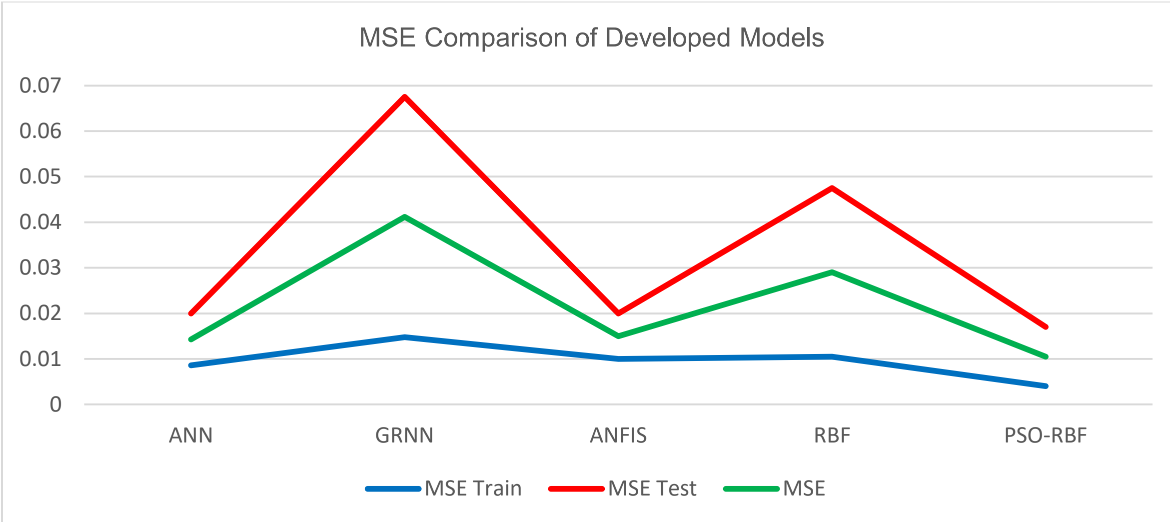


Figure 5-27. Comparison MSE for Different Algorithms.

From this comparison, the following can be concluded:

- PSO-RBFNN shows the highest R-squared in testing phase followed by ANN, RBFNN, ANFIS, and GRNN;
- ANN shows the highest R-squared in training phases followed by PSO-RBFNN, RBFNN ANFIS, and GRNN;
- GRNN is the least accurate technique among the other techniques for the given dataset in both training and testing phases;
- PSO-RBFNN has the lowest MSE among other techniques in training and testing phases followed by ANN; and

From Figures 5.27 and 5.28, it can be concluded that PSO-RBFNN has the best performance among other techniques. Moreover, the developed models were compared based on statistical performance indicators as shown in Table 5.17. Figures 5.27 and 5.28 show the outcome comparisons of all the AI-based models developed and discussed in this chapter. As can be seen in Figure 5.28, the RBFNN shows superior performance both in the training and testing phase. Another substantial result is that the developed model error is very close in both the training and testing phases. This demonstrates that the developed model shows good performance from generalization (Figure 5.31).

The model avoids both training data underfitting, which corresponds to high statistical bias and training data over-fitting, which corresponds to high statistical variance. Although the ANFIS shows considerable results in terms of generalization, ANIFS has lower accuracy as compared to the PSO-RBFNN. Thus, it can be concluded that the PSO-RBFNN model performs better in predicting labor productivity for the given dataset.

Table 5-17. Comparison of Statistical Performance Indicators for Different Algorithms.

Technique	R^2 Train	R^2 Test	R^2	MSE Train	MSE Test	MSE
ANN	0.954	0.701	0.906	0.0086	0.02	0.014
GRNN	0.88	0.64	0.760	0.0148	0.0675	0.041
ANFIS	0.89	0.66	0.775	0.01	0.02	0.015
RBF	0.81	0.67	0.740	0.0105	0.0475	0.029
PSO-RBF	0.969	0.891	0.93	0.004	0.019	0.011

5.9 Summary

This chapter discussed construction labor productivity modeling using three regression techniques and four AI techniques and as well as a proposed model based on RBFNN. A dataset for two high-rise building was adopted from Khan's (2005) study for developing productivity models. This chapter can be summarized into three main sections, outlined below. The first section outlined modeling labor productivity using BSR, STR, and EPR techniques. Among these regression models, EPR had a clear edge in terms of performance in comparison to the two other techniques. EPR is a non-linear stepwise regression method and does not need large datasets for model development. In addition, EPR provided an expression for the selected model to define the relationships between predictor variables and output. Although EPR has gained more attention and has been applied to different engineering areas due to its powerful ability to provide expression and genetic algorithms, to date, the technique has not been utilized for modeling labor productivity. Thus, expert knowledge and judgment were accompanied with the EPR technique to validate if the produced mathematical model and correlations between utilized predictor variables and response variable were realistic and practical. The second section covered the AI-based modeling techniques, namely ANN, GRNN, RBF, and ANFIS. The same dataset as in the previous section, was used to develop four labor productivity models employing the AI-based techniques. The developed ANN model showed much stronger performance in comparison to the other three techniques. An extensive trial and error approach were conducted to find the optimum ANN model architecture. Thus, an ANN model with two hidden layers with 20 neurons at each layer was selected. Although this technique shows acceptable performance, the black box is the main drawback of this approach. The third section covers a proposed AI-based model for modeling labor productivity. The developed model attempts to improve labor productivity prediction accuracy and shows reliable performance from the point of generalization due to having the training and testing errors close to each other. The developed model was based on the RBFNN technique, which was augmented by applying some data processing techniques such as expectation-maximization, normalization, and the resampling of raw datasets for enhancing the given dataset. Also, the developed model benefitted from PSO for optimizing RBFNN parameters as well as networks, which can be very useful for generalization. Finally, the developed model output was used as input for the developed SD model described in Chapter as baseline productivity.

6. CHAPTER SIX: SYSTEM DYNAMICS MODEL FOR QUANTIFYING LOSS OF PRODUCTIVITY

6.1 General Overview

Construction projects are extremely convoluted, highly dynamic, involve multiple feedback processes, have non-linear relationships, and include both hard and soft data. The high frequency of changes in conjunction with the increasing complexity of construction projects has shown that traditional project management tools are not capable of capturing the full picture of project management's strategic issues. Traditional project tools such as CPM and EVA have helped project management teams address the operational problems within a project. Meanwhile, SD modeling technique has provided more strategic and holistic views regarding the advantages and side effects of managerial policies. In other words, SD provides a more holistic view of the projects and enables to focus on the managerial policies and human factors that drive the project outcome. Furthermore, client-imposed changes may lead to costly ripple effects which can be a source of delay, disruption along with loss of productivity during the course of a project. To the best of my knowledge, at present, there is no mental model capable of quantifying the ripple effects of imposed changes or allocating responsibility for delay and disruption. In general, construction projects suffering from the "90% syndrome", where changes, reworks, and mistakes are kept until the end of the project. This issue necessitates costly rework, overtime, hiring new workforce, schedule pressure, removing parts of project scope, and degrading quality (Sterman, 1992).

This chapter covers the use of SD for modeling the impact of managerial policies and changes on labor productivity in heavy construction projects. The SD was employed in this research due to its capability of modeling elements and their interconnections in terms of a system using Causal Loop Diagrams (CLDs) and Stock Flow Diagrams (SFDs). CLDs and SFDs are a way of practicing systems thinking. In fact, system thinking goes beyond cause-effect relationships and consists of all the apparent and obscure surrounding variables in a complex system. CLDs can better generate a multidimensional loss of productivity model providing a more complete understanding of the relationships among construction project progress, changes and managerial decisions. In addition, SD has proven to be an effective analytical tool for quantitative assessment of complex problems, both hindsight and foresight approaches.

The results generated by the SD were compared with the ones obtained from Measured Mile Analysis (MMA) which is considered as a widely recognized and accepted technique for quantifying the loss of productivity as well as Leonard and Ibbs regression models. In the proposed model, the main sources of productivity loss were identified and CLDs and SFDs used to model complex behavior of construction project dynamics that neither Discrete Event Simulation (DES) nor Agent Based Modeling (ABM) can provide. DES is an event driven simulation which focuses on modeling certain processes at their operational level. On the other hand, ABM is useful for modeling behavioral characteristics and offers some descriptive understanding of the collective behavior of agents following sets of rules (Atef, 2015). As mentioned in Chapter 2, SD is useful because of the following reasons:

1. The system behavior follows a nonlinear pattern which is influenced by feedback loops;
2. The need to see the whole picture of the system rather than focusing on the individual elements;
3. Ability to explore the impact of different and multiple disruption events on productivity; and
4. Validates the CLDs in numerical terms and against the reference model at any stage of the project.

For developing an SD model and approximating the model parameters, it is highly recommended that all sources of information (such as the advantage of Controlled and uncontrolled experiments, Statistical information, Case studies, Expert knowledge, Stakeholder knowledge, Physical laws and Personal intuition) are taken in to account (Al-Kofahi, 2016). The following sections provide an overview of SD concepts, its modeling elements, and present the developed SD model. It should be noted that SD model is used for quantifying the impact of managerial decision on labor productivity. In other words, SD will provide a holistic view at the strategic level of construction projects.

6.2 Casual Loop Diagrams (CLDs)

CLDs are at the core of SD modeling. In a complex system, there are circular relationships between cause and effect that control the behavior of a system. Whereas the loss of productivity is a complex system consisting of various apparent and obscure influencing variables, to understand the behavior of this system, it is crucial to recognize the cause and effect relationships generating closed loops and to determine their boundary. CLDs allow project management teams to have better understating of the potential consequences of decisions and actions illustrated by feedback loops within the system. CLDs, including variables and causal links, show conceptual feedback structures of a system and are easy to understand. Two types of system can be presented by CLDs: closed system and open system. In SD, a closed system is one in which the causes generating the behavior of interest lie within the system. A closed system still is open in the sense that it can receive inputs from outside the boundary. Relationships or loops in CLDs can be either positive or negative. Positive loops are a series of causal connections that show a self-reinforcing process and create augmented results. In other words, a positive link shows that the dependent variable is directly relative to the cause, so that when the cause increases or decrease the dependent variable shows the same behavior. On the other side, a negative link (balancing feedback loop) designates that the dependent variable is inversely related to the cause, so that when the cause increases or decrease the dependent variable shows the opposite behavior. Therefore, feedback loops can be defined as a series of interconnected variables in which when a variable of this loop is varied, this variation circulates through the loop resulting in a variation to the initiating variable. A variation in initiating variables can cause two different states reinforcing a (positive) feedback loop or balancing a (negative) feedback loop. A reinforcing loop strengthens the original process, while a balancing loop stabilizes the original process (Atef, 2015). A system governed by negative feedback loops is expected to be at the state of equilibrium and resistance to perturbations within the system as well as to actions for improving project outcomes. Meanwhile, in a system controlled by positive feedback loops, it is possible to have a high degree of unsteadiness in which any actions or events may lead to major variations in project outcomes. For example, Figure 6.1 shows a simple project management CLD which is a negative feedback loop. If productivity is impaired and drops below planned productivity, schedule pressure will increase. Thus, schedule pressure will lead to the implementation of an overtime plan by the project management team, which will increase productivity and reduce schedule pressure. The main advantage of building CLDs is the fact that different mental models regarding the same issue can be captured and compared. In the case of loss of productivity, project parties can disagree on how productivity is impaired; this is because project parties often have diverse mental models of the system where the problem is implanted (Kim, 1992).

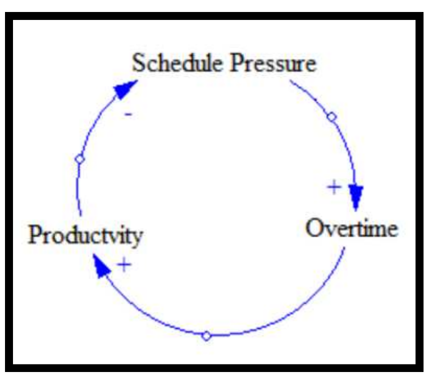


Figure 6-1. Simple CLDs.

6.3 Stock Flow Diagrams (SFDs)

After developing CLDs, an SFD was developed and fundamental mathematical equations among variables that constitute the structure of the model were added. SFDs along with CLDs are two central concepts of SD. Stock is the representation of variables with accumulation and flows represent variables that cause the accumulations (rates of accumulation). The value of stock variables fluctuates during simulation through variations of its inflow and outflow variables. Therefore, stocks let decisions to be made and flows show changes in the system under study. Figure 6.2 shows the symbols of an SFD.

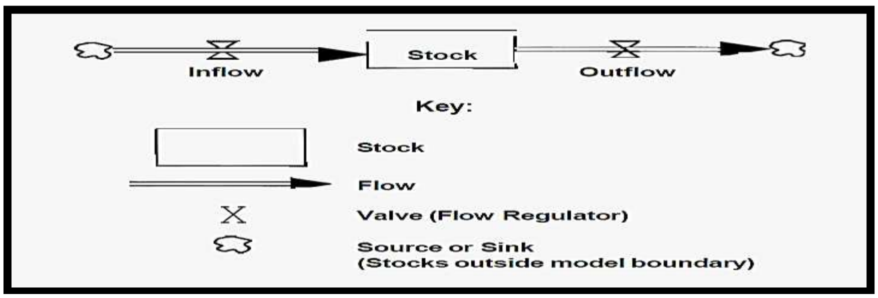


Figure 6-2. Stock Flow Diagrams Notation.

6.4 Problem Identification

Change orders are the only constant of construction projects and these changes may affect labor productivity adversely. Change orders lead to the need to hire more workers to improve productivity to meet key project milestones, resulting in project cost increase. However, hiring more workers might not improve productivity as expected because the relationship between change orders, managerial policies, and labor productivity are not tangible and not well understood. This chapter emphasizes the impact of change orders and managerial policies on labor productivity, the importance of quantifying productivity loss, and linking this loss to main causes. In the next sections, the developed SD model components will be explained in detail.

6.5 Model Boundary Identification

Prior to the generation of CLDs, the main variables contributing to the loss of productivity were identified. The behavior of the system was created inside a limited boundary during the feedback processes in the SD model. The extent of the model is summarized by the model boundary which categorizes the key factors by identifying endogenous, exogenous, and excluded variables. The model boundary shows the variables used in the SD model and used to study the sub-system's feedback, as shown in Tables 6.1 and 6.2. A set of exogenous variables is shown in Table 6.2 which was the input to the developed SD model, allowing the dynamic behavior of endogenous variables to be modeled. These tables summarize the scope of the model by presenting the important endogenous and exogenous variables which enable exploring the behavior patterns created by the mathematical rules among them and learning how the behavior of a system may change if those rules are changed. An exogenous variable is an independent variable that is external to the SD model. A variation in an exogenous variable can cause change or impact on endogenous or dependent variables. In other words, the values of exogenous variables are not affected directly by the system (Sterman, 2000). Endogenous variables are the most crucial factors among all model factors in a cause and effect structure whose value is dependent on the states of other variables in the system. Endogenous variables typically reflect the procedures embedded in systems. Examples of such variables in construction projects are fatigue, required overtime, error, and quality. On the contrary, exogenous variables are external factors that are undefined by the model's feedback mechanism. These variables' value, in the cause and effect structure, is determined independently from the states of other variables in the system. Therefore, the system's internal interactions do not affect the exogenous factors. Examples of exogenous variables are planned project duration and baseline productivity. Excluded variables are beyond the scope of the developed model and have no substantial effect on the model representation. Consequently, they were not considered in the developed model; however, excluded variables should be included in the system if they tend to influence the model. It is essential to recognize the necessary and unnecessary variables in the model and include or exclude them accordingly; otherwise, redundant variables in a system can create chaos in the development of a comprehensive model.

Table 6-1. Model Exogenous Variables.

No	Variable Names
1	Baseline Productivity
2	Baseline Quality
3	Mean Time to Approve Changes
4	Initial Quantity of Work
5	Mean Time to Discover Nonconformity Report (NCR)
6	Average Time to Detect Defect
7	Relative Quality of New Hires
8	Quality of Overtime Manpower
9	Standard Workweek
11	Overtime Policy
14	Time to Hire
15	Learning Curve Rate
16	Planned Manpower
17	Average Hourly Cost
18	Number of Week Overtime
19	Actual Crew Size
20	Optimum Crew Size
21	Target Delivery Time
22	Number of Disruption Days

Table 6-2. Model Endogenous Variables.

No	Variable Names
1	Quality
2	Productivity
3	Percentage of Changes
4	Loss of Productivity
5	Rework Discovery Rate
6	Discovered rework
7	Feasible Accomplishment rate
8	Minimum Time to Accomplish Work
9	Maximum Accomplishment Rate
10	Potential Work Rate
11	Additional Manpower Required
12	NCR Generation Rate
13	Impact of Overtime and New Hires on Quality
14	Quality of Overtime Workforce
15	Effect of Overtime on Productivity
16	Impact of Learning Curve on Productivity
17	Number of New Hires
18	Additional Workforce Required
19	Cumulative Work to Be Done
20	Remaining Quantity of Work to Be Done
21	Quantity of Work Completed
22	Work Accomplished Rate
23	Effect of Learning Curve on Productivity
24	Current Manpower Level
25	Cumulative Labor Cost
26	Overmanning
27	Crowding
28	Identified Changes
29	Approved Changes
30	Completed Changes

6.6 Modeling Assumptions

In this section, the proposed SD model development is explained stepwise. “Remaining Quantity of Work to Be Done” and “Quantity of Work Completed”, which are linked by “Work Accomplished Rate”. When starting to accomplish work, “Remaining Quantity of Work to Be Done” begins to drop from its initial value while “Quantity of Work Completed” variable starts to increase from its initial value of zero.

The rate at which “Remaining Quantity of Work to Be Done” reduces and the “Quantity of Work Completed” accumulates is determined by the variable “Work Accomplished Rate”. The following equations demonstrate the dynamics of the basic accomplishment model:

$$Remaining\ Quantity\ of\ Work\ to\ Be\ Done = Initial\ Quantity\ of\ Work\ to\ Be\ Done - \int_0^T (Work\ Accomplishment\ Rate)dt \qquad Equation\ 6.1$$

and,

$$Quantity\ of\ Work\ Completed = 0 + \int_0^T (Work\ Accomplishment\ Rate)dt \qquad Equation\ 6.2$$

Where, T is the duration conveying the process during which “Remaining Quantity of Work to Be Done” is tended to zero and “Quantity of Work Completed” is tended to “Initial Quantity of Work to Be Done”. Equations 6.1 and 6.2 were solved numerically by employing Euler or Rungi-Kutta Numerical Integration methods in Vensim software (Ventana System, 2018).

6.6.1 Rework and Quality Feedback Loops

The aforementioned model assumes that the work is accomplished under perfect conditions and nonconformity was not generated as the work progresses. However, nonconformities are always generated as a part of project advancement and captured by QA/QC in the form of nonconformity report (NCR). NCR shows the amount of rework and repair in a construction project.

In addition, percentage of NCR in construction projects shows the quality of accomplished work. Therefore, the previous model needed to be modified to include a loop for rework (Aiyetan and Das, 2014). According to the Australian Construction Industry Development Agency (CIDA), rework can be defined as “doing something at least one extra time due to non-conformance to the requirements” (CIDA, 2001).

Repair is considered to include rework, as it is a process of restoring a nonconforming characteristic to a satisfactory condition even though the item may not still match to the agreed requirement in drawings and specifications. Rework may lead to schedule slippage and cost overrun being the source of many project management challenges (Ballard et al., 2001; Lyneis and Ford: 2007).

It should be noted that at each iteration during the simulation, “Quantity of Work Completed” contains both defect free work and defected work (Figure 6.3). The defected work must be considered as rework and sent back to “Remaining Quantity of Work to Be Done”.

To attain a more realistic model, two more variables needed to be added to the SD model: NCR Generation Rate and Rework Discovery Rate. Therefore, Equation 6.1 was modified to reflect the effect of rework generation loop, as can be seen in Equation 6.3 and 6.4.

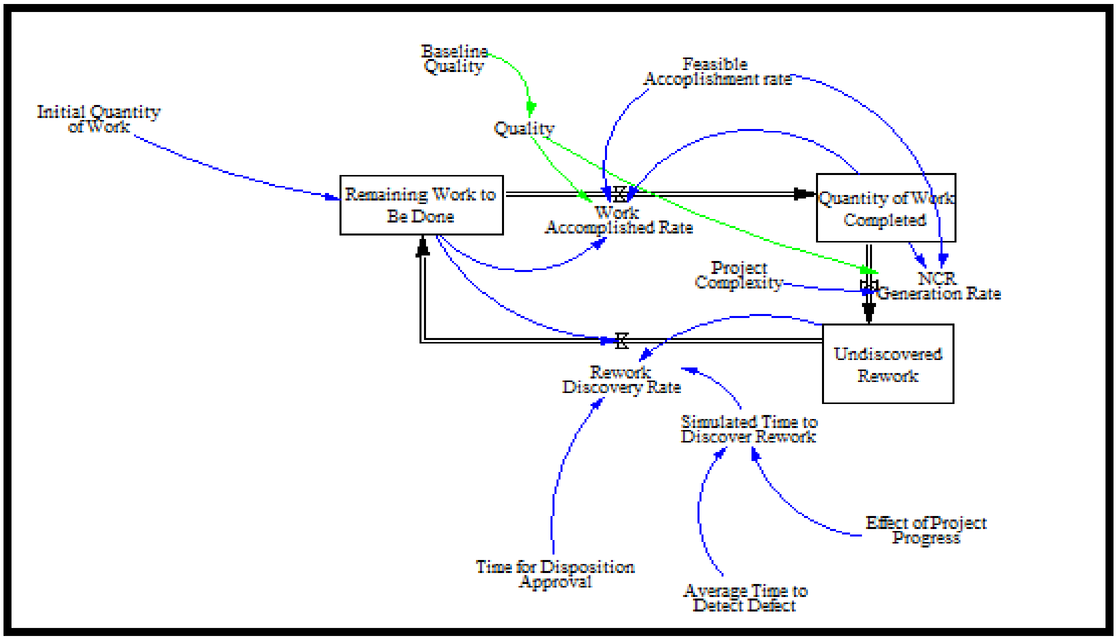


Figure 6-3. Impact of Rework Feedback Loop.

$$Remaining\ Quantity\ of\ Work\ to\ Be\ Done$$
$$= Initial\ Quantity\ of\ Work\ to\ Be\ Done + Rework\ Discovery\ Rate$$
$$- \int_0^T (Work\ Accomplishment\ Rate) \qquad Equation\ 6.3$$

$$Quantity\ of\ Work\ Completed$$
$$= \int_0^T (Work\ Accomplishment\ Rate)$$
$$- (NCR\ Generation\ Rate) \qquad Equation\ 6.4$$

The following Equations were included for quality dependent variables (Equation 6.5 to 6.8):

$$Work\ Accomplishment\ Rate$$
$$= \ Feasible\ Accomplishment\ Rate * Quality \qquad Equaition\ 6.5$$

$$NCR\ Generation\ Rate \ = \ Feasible\ Accomplishment\ Rate\ (1 - Quality) \qquad Equaition\ 6.6$$

$$Rework\ Discovery\ Rate$$
$$= \frac{Discovred\ Rework}{Stimulate\ Time\ To\ Discover\ Reowrk + Time\ for\ Disposition\ Approval} \quad Equaition\ 6.7$$

$$Undiscovred\ Reowrk = \int_0^T (NCR\ Generation\ Rate\ \ - Rework\ Discovery\ Rate)\ dt \ \ Equation\ 6.8$$

Construction quality is a function of several variables. In this research, quality is defined as the percentage of accomplished work at each iteration that conforms to the completed work according to the required specifications. The part of work that did not meet project specifications was considered a defect resulting in rework. As can be seen from Figure 6.4, factors affecting the quality are as Baseline Quality, Overtime Work, New Hires Learning Curve, and Relative Quality of New Hires.

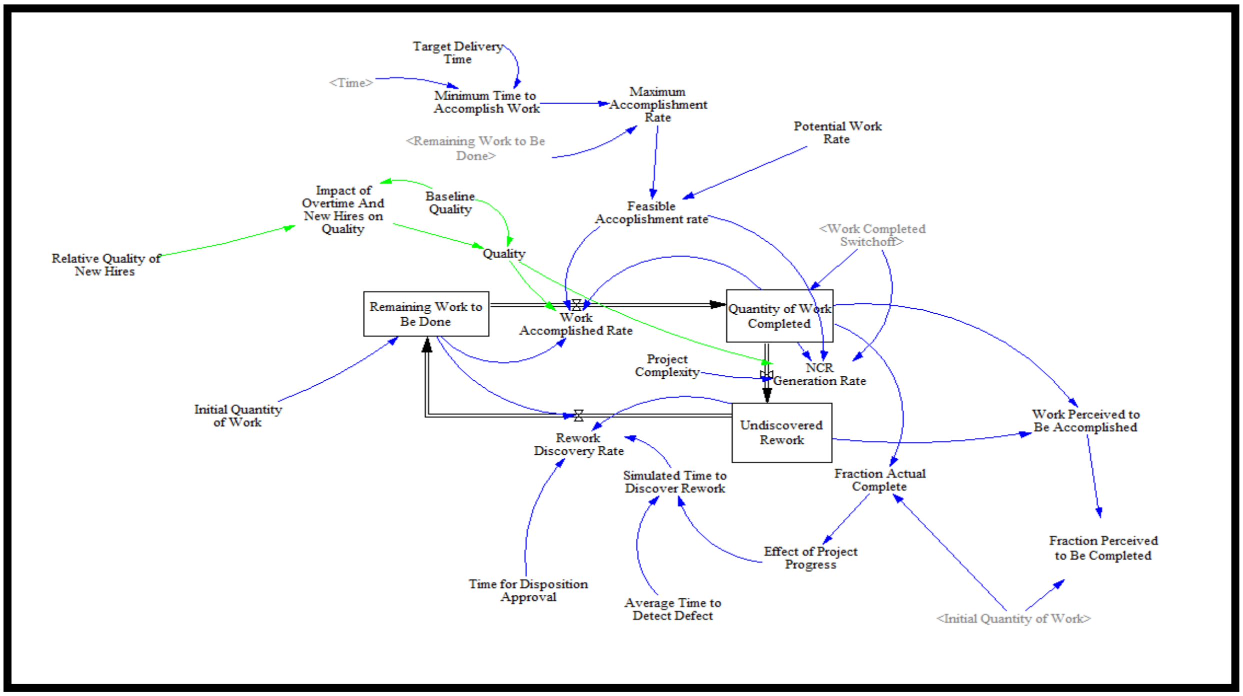


Figure 6-4. Impact of Quality Feedback Loop.

Baseline Quality is an exogenous variable that defines the quality of work considered in the initial estimate of the project. It should be noted that Quality is an endogenous variable whose behavior is contingent upon the two factors presented in Figure 6.4. Equation 6.9 shows the effect of New Hire and Overtime on Quality:

$$Quality = Baseline\ Quaility$$
$$* \ Impact\ of\ New\ Hires\ and\ Overtime\ on\ Quality \qquad Equation\ 6.9$$

6.6.2 Productivity Feedback Loops

As mentioned in Chapter 2, productivity can be defined in several ways. For example, productivity is the amount of work accomplished to the amount of resources spent such as time or money. In this research, productivity is expressed as a ratio between output quantity and input quantity. Productivity behavior can be influenced by several factors such as Overtime, Learning Curve of New Hires, Overmanning, Trade Stacking, Temperature, and Humidity. All these variables have a negative impact on productivity. For more clarification, it should be noted that the abovementioned variables are somehow connected to an acceleration plan in construction projects. Once changes are introduced to a project, the "Remaining Quantity of Work to Be Done" changes or "Quantity of Work Completed" might need to be reworked. To mitigate delay in the project and meet project deadlines, project parties might implement some corrective actions such as project acceleration which is the most common action. Acceleration can be accomplished through several methods, including overtime, increasing manpower, changing work sequences, and increasing working shifts (Schwartzkopf, 2004). Although each of these acceleration methods will improve production, it should be noted that there is an inherent loss of productivity associated with each of these acceleration methods. For example, extensive continuous overtime will cause workforce fatigue, resulting in loss of productivity or having many laborers on a job site will lead to overcrowding which leads to less available workspace per labor and can cause loss of productivity as well. As new laborers join the workforce, time is needed to get familiar with the assigned work and meet expected productivity. These variables are explained in more detail in the following sections:

- Overtime: Overtime is the simplest way to accelerate a project. Overtime is the use of more than 40 man-hours per week labor. Overtime can be useful for rectifying situations such as handling unexpected problems or finishing critical activities, as well as overcoming delays by producing more work in an agreed number of days while working more hours per day or more days per week. Overtime can be employed to shorten the agreed project duration or used to attract workers because the working overtime results in higher earning for workers. Furthermore, overtime can be used to take advantage of favorable weather to maximize the use of workforce and equipment. Overtime will result in more costs and reduce productivity. Overtime is paid at a premium wage rate such as time and a half or double time. Overtime has some negative effects on the project including but not limited to: increased absenteeism, more safety incidents, and inadequate quality (Schwartzkopf, 2004). Overtime can be classified into two categories:

  i) spot overtime and ii) scheduled or extended overtime. Spot overtime is used to cover unexpected changes or to complete critical activities. Scheduled or extended overtime is used as a motivation to absorb more laborers or efforts to deliver a project earlier than what agreed upon in the project contract.

  There are the considerable number of studies conducted on the effects of overtime on productivity including studies published by the National Electrical Contractors Association (NECA), Mechanical Contractors Association of America (MCAA), and Construction Industry Institute (CII) (Table 6.3).

Table 6-3. Scheduled Overtime Impact on Productivity (MCAA, 2016).

No. Week OT	50 hrs./wk.	55 hrs./wk.	60 hrs./wk.	63 hrs./wk.	70 hrs/wk.	84 hrs./wk.
1	0.95	0.94	0.91	0.89	0.86	0.75
2	0.93	0.9	0.88	0.84	0.8	0.7
3	0.92	0.86	0.85	0.78	0.73	0.65
4	0.91	0.83	0.81	0.73	0.68	0.6
5	0.85	0.79	0.76	0.67	0.63	0.55
6	0.86	0.75	0.72	0.62	0.58	0.5
7	0.78	0.72	0.67	0.58	0.54	0.47
8	0.77	0.7	0.64	0.55	0.51	0.44
9	0.74	0.68	0.62	0.54	0.5	0.43
10	0.72	0.66	0.61	0.52	0.49	0.42
11	0.72	0.65	0.6	0.51	0.48	0.41
12	0.71	0.64	0.59	0.5	0.47	0.4
13	0.69	0.63	0.56	0.49	0.46	0.39
14	0.68	0.62	0.55	0.48	0.45	0.38
15	0.67	0.61	0.54	0.47	0.44	0.37
16	0.66	0.6	0.53	0.46	0.43	0.36

To include Table 6.3 into the SD model, the following steps were taken (Figure 6.5). Calculate the percentage of overtime by using the following Equation:

$$\%\ of\ Overtime = \frac{Working\ Hours\ per\ Week}{Normal\ Hours\ per\ Week} \qquad Equation\ 6.10$$

Where, Working Hours per Week was considered to be 50, 55, 60, 63, 70, and 84 hours week. Normal Hours per Week was assumed to be 40 hours per week. For example, 50 hours per week means overtime by 25%; and

1. Each overtime variable was modeled separately using the lookup table, as shown in Figure 6.5. This approach allows the analyst to select different overtime policies and quantifying the impact of selected policy on productivity.

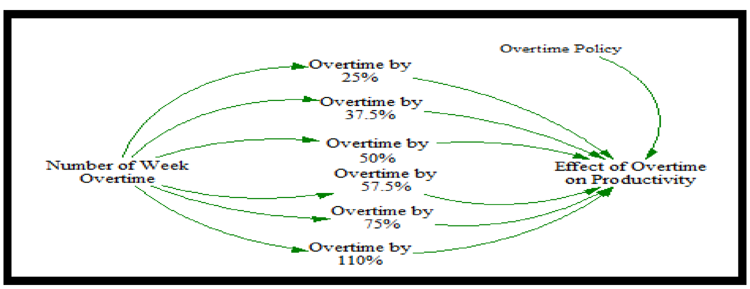


Figure 6-5. Modeling Effect of Overtime on Productivity.

- Overmanning: Increasing the number of men on a crew over the optimum level on a project. Overmanning may cause the loss of productivity. U.S. Army Corps of Engineers (USCAE) (1979) defines the optimum crew size as the minimum number of workers needed to complete the task within the assigned time frame. Figure 6.6 is provided by

USCAE for estimating the loss of productivity due to overmanning. The crew percentage size increase is calculated by dividing the optimum crew size by the actual size of crew minus 1 and multiplying by 100% (Equation 6.11):

$$\%\ Crew\ Size\ Increase = \left(\left(\frac{Actual\ Crew\ Size}{Optimum\ Crew\ Size}\right) - 1\right) * 100\% \qquad Equation\ 6.11$$

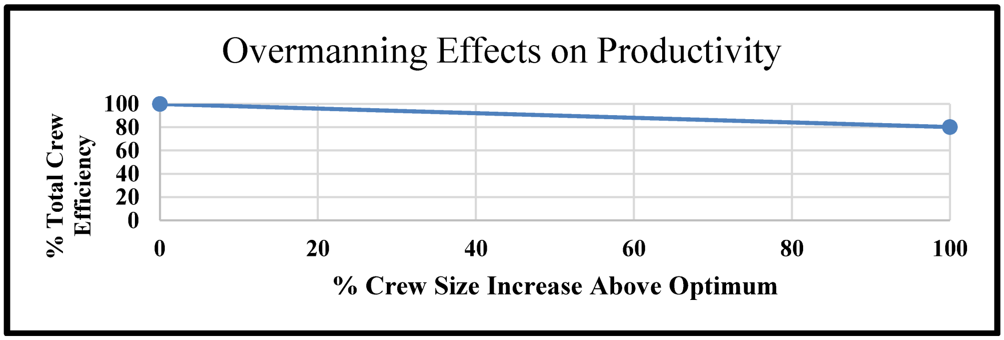


Figure 6-6. Overmanning vs Productivity (USACE, 1979).

- Trade Stacking: When a work area becomes crowded with different trades due to acceleration (Figure 6.7). This will occur when construction sequences allow overlapping of work areas. Loss of productivity occurs due to crowding of different trades assigned to a particular work area.

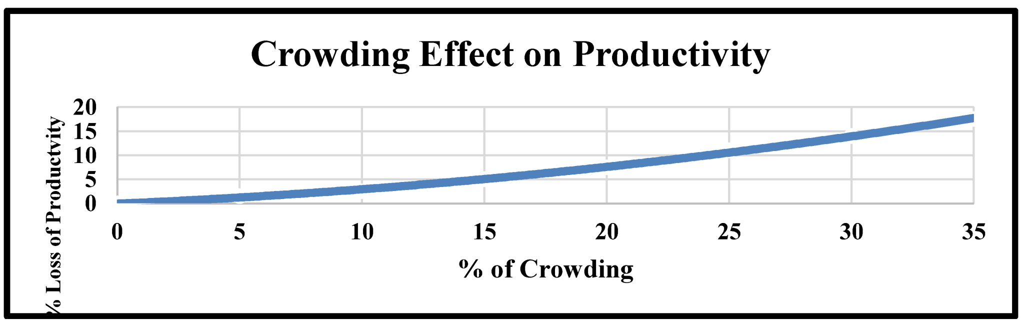


Figure 6-7. Trade Stacking vs Productivity (USACE, 1979).

The crowding percentage (Equation 6.12) was calculated by dividing the planned manpower by the actual manpower minus 1, and multiplying by 100% (Schwartzkopf, 2004)

$$\%\ Crowding = \left(\left(\frac{Actual\ Manpower}{Planned\ Manpower}\right) - 1\right) * 100\% \qquad Equation\ 6.12$$

It should be noted that the USCAE assumes that planned manpower is the optimum value for manpower. Figure 6.7. has not been released by USCAE. Thus, it is unknown if the graph was developed using crisp data (Schwartzkopf, 2004). In the developed model actual manpower is represented by “Current Manpower Level”.

- Learning Curve: MCAA defines a learning curve as the "Period of orientation in order to become familiar with the changed condition. If new men are added to the project, it results in severe effects, as they require learning tools, locations, work procedures, etc. The effects of the learning curve can be considered for workers joining the project at the beginning of the contract, newly hired during the course of a project, or starting work in a very different environment. Workforce productivity is anticipated to be increased when workers get more familiar with the project or their tasks. Thus, the effect of the learning curve on labor productivity is limited to the beginning days or weeks of the project. It should be noted that the learning curve is a double-edged sword. It means that the learning curve has both negative and positive effects. The positive effect occurs when the workforce acquires the knowledge, training, and skills relating to a specialized trade and the work is done in a more effective and efficient manner. The negative effect of the learning curve occurs if the work is delayed or disrupted and the work executed by the newly hired workforce after the delay and disruption is not equal to the productivity rate as before the disruption. Understood in a different way, the negative effects of a learning curve are caused by disremembering of work related to the length of the disruption (Schwartzkopf, 2004). In this research, the negative effect of a learning curve was considered, and the value of efficiency assumed to depend on the complexity of the job, as shown in Table 6.4 (MCAA, 2016).

Table 6-4. The Effect of Learning on Productivity.

	Percentage of Efficiency		
Learning Curve Effect	Minor	Average	Severe
	5%	15%	30%

- Temperature and Humidity: Adverse weather conditions can be detrimental to the success of construction projects. There are many examples of the effects of overlooking the impact of weather conditions on labor productivity in the construction industry. Construction projects are influenced by adverse weather conditions negatively and good weather conditions positively. Construction labor productivity can be affected by elevated temperatures, low temperatures, humidity, and precipitations. Changes from good weather conditions to adverse weather conditions can result in loss of productivity. Several studies were conducted to show the effect of weather conditions on labor productivity, such as the British Building Research Station (BBRS) study, US Army Cold Regions Research and Engineering Laboratory, and the National Electrical Contractors

Association (NCEA). According to the NCEA study, labor productivity will decrease when the temperature goes above 27ºC and below 4ºC, and at relative humidity rates above 80%, especially for high temperature. This means that humidity becomes a significant factor affecting labor productivity when combined with either very high or very low temperature (Koehn and Brown, 1985). In this research, Kohen and Brown’s dataset was used, which is a combination of NECA (1974) and Grimm and Wagner (1974) datasets for showing the impact of temperature and humidity on labor productivity, as shown Table 6.5.

Table 6-5. Productivity as a function of temperature and relative humidity.

	Relative Humidity (%)									
Temp. (F)	5	15	25	35	45	55	65	75	85	95
-20	0.28	0.27	0.25	0.22	0.18	0.13	0.05	0.05	0.05	0.05
-10	0.44	0.43	0.42	0.4	0.38	0.34	0.29	0.21	0.1	0.1
1	0.59	0.58	0.57	0.56	0.54	0.52	0.49	0.44	0.36	0.23
10	0.71	0.71	0.7	0.7	0.69	0.67	0.65	0.62	0.58	0.5
20	0.81	0.81	0.81	0.81	0.81	0.8	0.79	0.77	0.75	0.71
30	0.9	0.9	0.9	0.9	0.9	0.89	0.89	0.89	0.88	0.87
40	0.96	0.96	0.96	0.96	0.96	0.96	0.96	0.96	0.96	0.96
50	1	1	1	1	1	1	1	1	1	1
60	1	1	1	1	1	1	1	1	1	1
70	1	1	1	1	1	1	1	1	1	1
80	1	1	1	1	1	0.99	0.98	0.96	0.95	1
90	0.95	0.95	0.94	0.93	0.92	0.9	0.88	0.85	0.82	0.93
100	0.81	0.81	0.8	0.79	0.77	0.74	0.71	0.67	0.61	0.78
110	0.58	0.58	0.58	0.57	0.55	0.51	0.47	0.41	0.32	0.54
120	0.58	0.28	0.28	0.28	0.25	0.21	0.15	0.07	0.07	0.21

Note, productivity is an endogenous variable, but BP is an exogenous variable. BP was quantified using the developed model proposed in Chapter 5. Equation 6.13 shows the effect of abovementioned variables on productivity (Equation 6.13):

$$\begin{aligned} Productivity = {} & Baseline\ Peoductivity \\ & * (1 + Impact\ of\ Learning\ Curve\ of\ New\ Hires + Effect\ of\ Overtime \\ & + Impact\ of\ Overmanning + Effect\ of\ Crowding \\ & + Effect\ of\ Temperature\ \&\ Humidity) \qquad Equation\ 6.13 \end{aligned}$$

Equation 6.13 is supported by Thomas et al., (1990) who developed a conceptual model for forecasting loss of productivity considering various influencing factors illustrated in Equation 6.14. Their model was based on field observation and actual empirical data. Loss of productivity was measured against undisturbed productivity or BP by considering both factors affecting productivity and their relative occurrence frequencies. The occurrence frequency represents the probability of occurrence of factors influencing productivity. By considering the frequency of these factors, albeit some of these factors may have severe impacts, the frequency of these factors is less. On the other hand, the factors with low impact may have a high frequency.

$$Productivity = Baseline\ Peoductivity * \left(1 + \sum_{i=n}^{n} f_i R_i\right) \qquad Equation\ 6.14$$

Where, f_i is the relative frequency of factor i, R_i is the relative average impact of factor I and n is the number of factors included in the model. In this research, influencing factors' frequency of occurrence was not included in the SD model. The occurrence frequency needs more investigation and is out of the scope of this research. The final developed productivity feedback loop is illustrated in Figure 6.8.

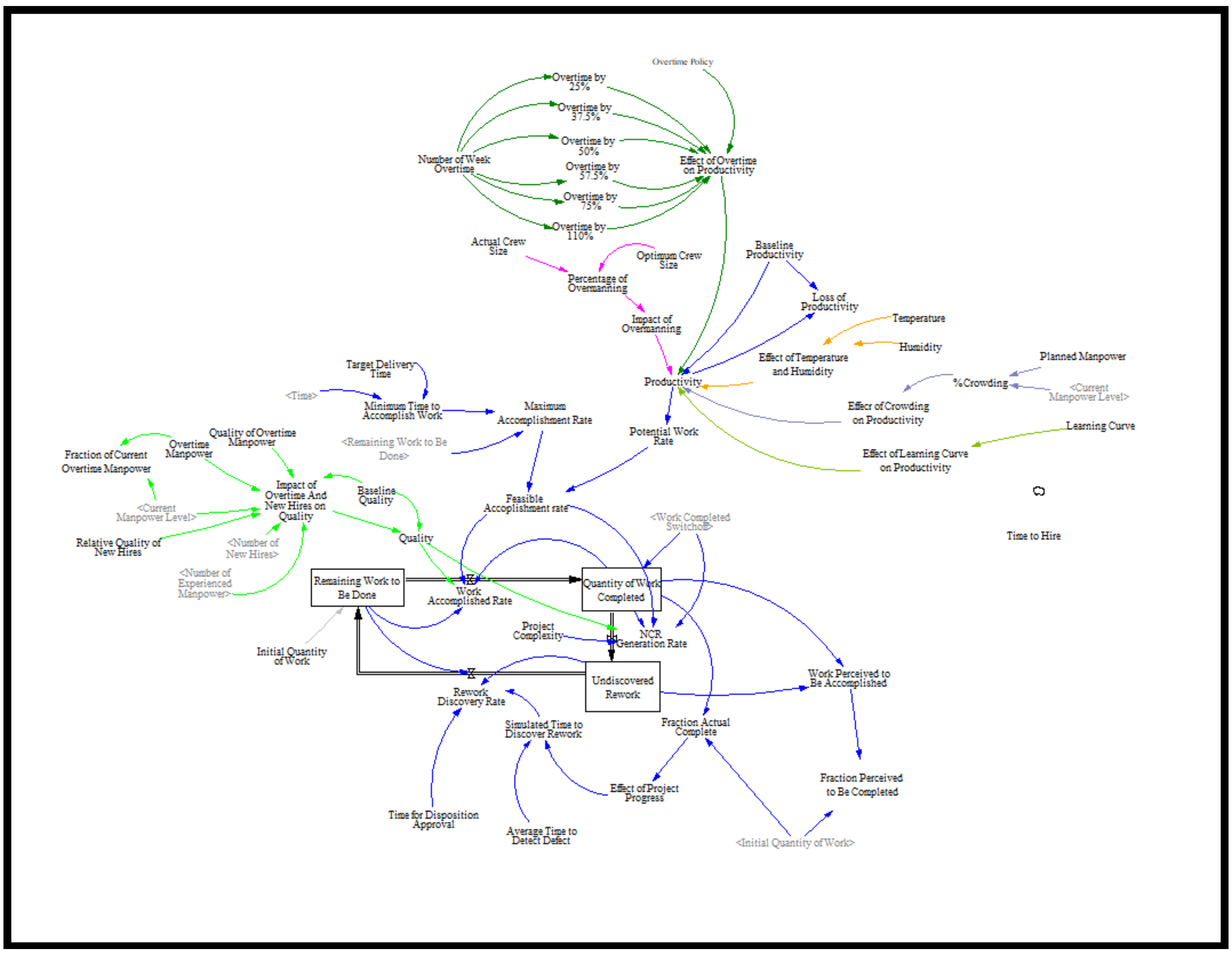


Figure 6-8. Productivity Feedback Loop.

6.6.3 Hiring Feedback Loops

Hiring feedback loops and equations are discussed in this section. As mentioned in the previous section, an increase in the workforce amount is one of the acceleration techniques. Figure 6.9

shows the hiring feedback loop; the shadow variables were used to simplify the graphical presentation of the developed SD model.

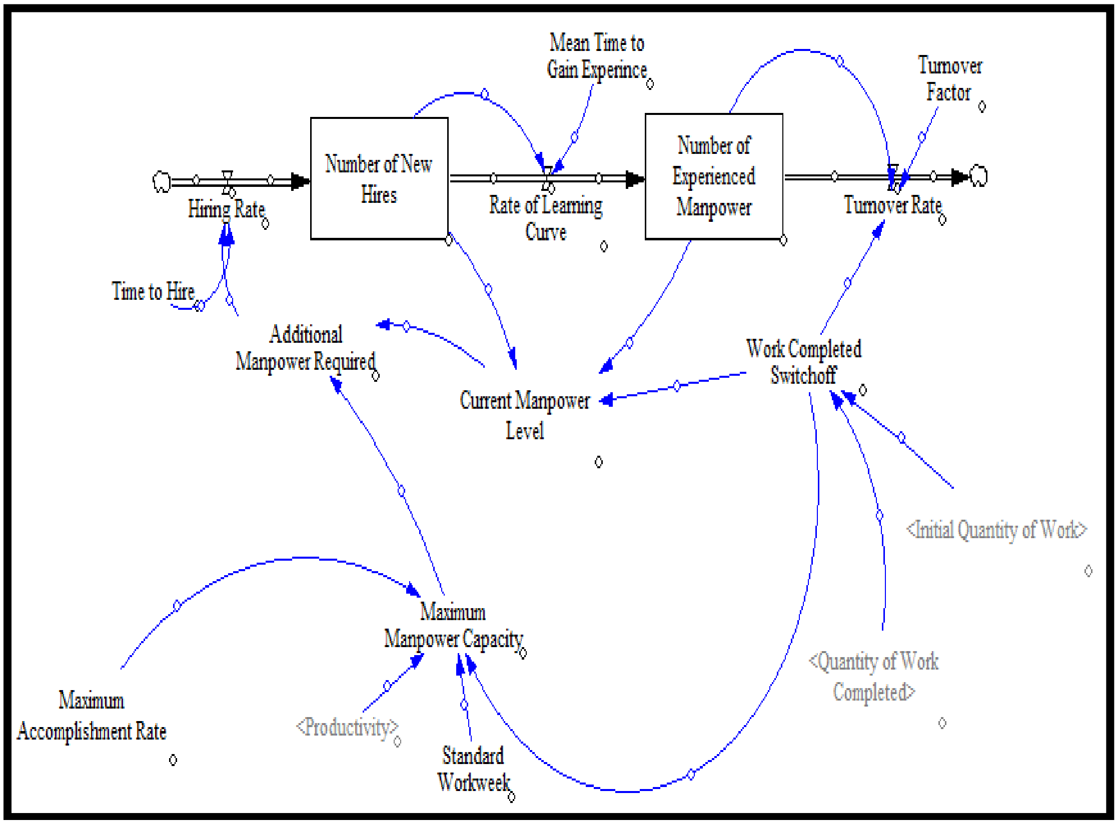


Figure 6-9. The Hiring Feedback Loop.

The number of New Hires was calculated by the following equation:

$$Number\ of\ New\ Hires = \int_0^t (Hiring\ Rate)\,dt \qquad Equation\ 6.15$$

As mentioned before, the learning curve can have a positive effect on the newly hired manpower getting familiar with the project. As new hires gain enough experience (Rate of Learning Curve), they can be considered as experienced manpower. Equation 6.15 was modified to reflect the positive effects of the learning curve, as shown in Equation 6.16):

$$Number\ of\ New\ Hires = \int_0^t (Hiring\ Rate - Rate\ of\ Learning\ Curve)dt \qquad Equation\ 6.16$$

Where, Hiring Rate is equal to the following equation (Equation 6.17):

$$Hiring\ Rate = \frac{Additional\ Manpower\ Required}{Time\ to\ Hire} \qquad Equantion\ 6.17$$

Correspondingly, New Hires and Overtime have an impact on Quality as well which were included in the developed SD model as follows:

$$Impact\ of\ New\ Hires\ on\ Quality$$
$$= ((Number\ of\ New\ Hires * Relative\ Quality\ of\ New\ Hires$$
$$+ Overtime\ Manpower\ * \left(\frac{Quality\ of\ Overtime\ Manpower}{Baseline\ Quality}\right)$$
$$+ (Current\ Manpower - Number\ of\ New\ Hires))$$
$$/(Current\ Manpower\ ) \qquad Equantion\ 6.18$$

6.6.4 Change Orders Feedback Loops

As mentioned before, change orders may occur as a result of substandard work quality, schedule delay, defects, incomplete design, scope changes caused by the client, and rework. It should be noted that scope changes may not be the sole cause of productivity loss; it is possible that other factors may contribute to loss of productivity. The following factors were determined to have considerable influence on whether a project may be impacted by change orders (Schwartzkopf, 2004):

- The percentage of change orders;
- The planned maximum manpower compared to the actual maximum manpower;
- The processing time of changes; and
- The maximum manpower divided by average manpower.

Factors contributing to the unfavorable impact of change orders on labor productivity were identified by Moselhi et al., (2005) as follows:

- Intensity: This factor covers the number of change orders, frequency of change orders, and the ratio of change order hours to planned or initial hours of the project;
- Timing: The timing of a change order has been addressed by several prominent researchers such as Moselhi et al., (2005), Ibbs (2005), Henna et al. (1999);
- Type of work: Type of work may influence the strength of the impact of change orders on labor productivity due to the complexity level and skill required to perform the work as well as the interdependency that differs from one type of work to another (Coffman 1997; Leonard 1988);

- Type of impact: This factor shows that loss of productivity is limited to only change orders or loss of productivity is caused as a result of the combination of other productivity-related factors such as overtime, crowding, learning curve, and weather conditions;
- Project phase: This factor divides the project into two phases “design phases and construction phases”; and
- On-site management: This factor considers the amount of experience possessed by project managers.

Majority of above-mentioned factors were included in the SD model in this chapter except for the project phase. In this research, however, it was assumed that the developed SD model covered only the construction phase and on-site management skill presented by Management Disruption Index (MDI) as will be discussed in section 6.5.5. MDI is restricted to the policies taken during the course of the project which may cause loss of productivity.

For the timing of change orders, Ibbs’ (2005) study was adopted and included in the developed SD model. Ibbs attempted to show the impact of a change’s timing on labor productivity. His regression model was developed based on data gathered from 162 construction projects over a nine-year period. Project value ranged from US 3.9 million to 14.5 billion dollars. As a result, three (3) curves were generated to illustrate the impact of change (from 0 to 60%) with respect to timing situations, early, normal, and late.

The mathematical representations are provided as Equations 6.19, 6.20, and 6.21 for early, normal, and late change, respectively:

$$Y_{early} = 1.0511 * e^{-1.0228X} \qquad Equation\ 6.19$$

$$Y_{normal} = 2.04221X^2 - 1.9234X + 1.0471 \qquad Equation\ 6.20$$

$$Y_{late} = 1.0511 * e^{-1.0228X} \qquad Equation\ 6.21$$

To incorporate Ibbs’s study, the following assumptions were made (Table 6.6). These numbers can be adjusted as per user preference and project characteristics. The SD model for considering the timing of change orders is shown in Figure 10.

Table 6-6. Project Progress and Phases.

Project Progress (%)	**Project Phase**
0-30	Early
31-70	Normal
71-100	Late

By including change order feedback loops, the “Quantity of Work Completed” will be higher than “Initial Quantity of Work to Be Done” during the course of a project. As mentioned before, the difference is the number of changes that are critical to quantify the loss of productivity and the cost associated with it. The following equations were used to determine the number of change orders as shown in Figure 6.10. Equations 6.22 – 6.27 were used to define scope change orders feedback loops.

$$Identfied\ Changes = \int_0^T (Rate\ of\ Identify\ Changes - Rate\ of\ Approaval)\ dt \qquad Equation\ 6.22$$

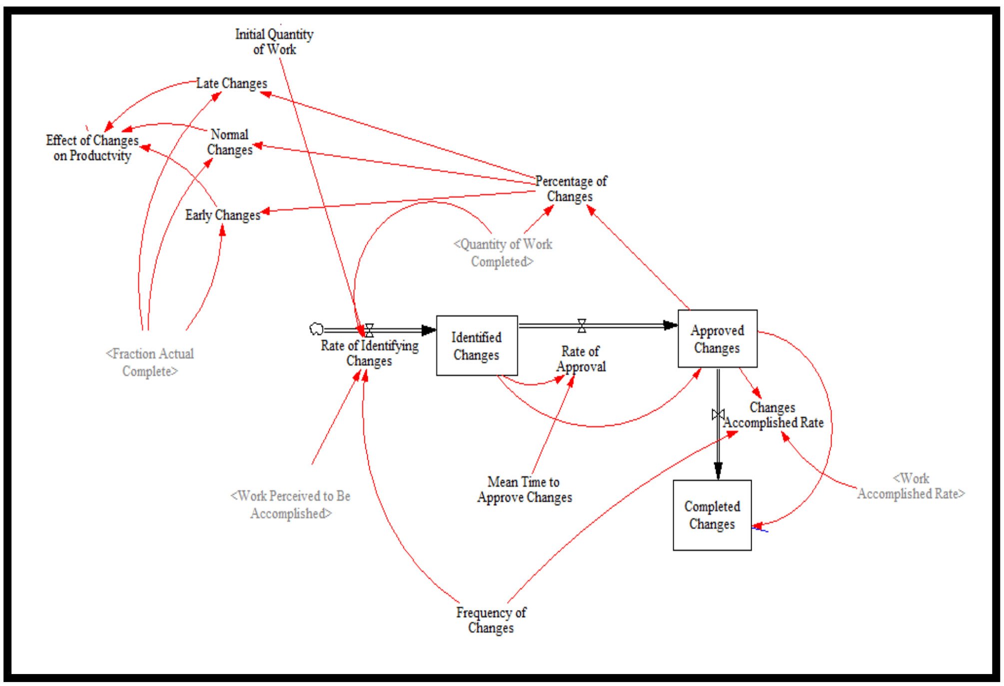


Figure 6-10. Changes Orders Feedback Loops.

$$Rate\ of\ Identify\ Changes = Frequency\ of\ Changes * Work\ Percviced\ to\ Be\ Accomplished \qquad Equation\ 6.23$$

$$Approved\ Change\ Orders = \int_0^T (Rate\ of\ Approval - Changes\ Accomplished\ Rate)\ dt \qquad Equation\ 6.24$$

$$Rate\ of\ Approval = Mean\ Time\ to\ Approve\ Change \qquad Equation\ 6.25$$

$$Completed\ Changes\ = \int_0^T (Changes\ Accomplished\ Rate)\, dt \qquad Equation\ 6.26$$

$$Changes\ Accomplished\ Rate = Frequency\ of\ Changes * Work\ Accomplished\ Rate \qquad Equation\ 6.27$$

Where, “Mean Time to Approve Change” and “Frequency of Changes” were calculated using the developed model discussed in Chapter 4. After calculating the Loss of Productivity amount, Loss of Productivity Cost was calculated as follows:

$$Loss\ of\ Productivity\ Cost = \int_0^T (Loss\ Hours\ rate)\, dt * Average\ Hourly\ Cost \qquad Equation\ 6.28$$

$$Loss\ Hours\ Rate = Quantity\ of\ Work\ Completed * Avaearge\ Loss\ of\ Productvity \qquad Equation\ 6.29$$

Loss of Productivity Cost was included in the developed SD model as shown in Figure 6.11.

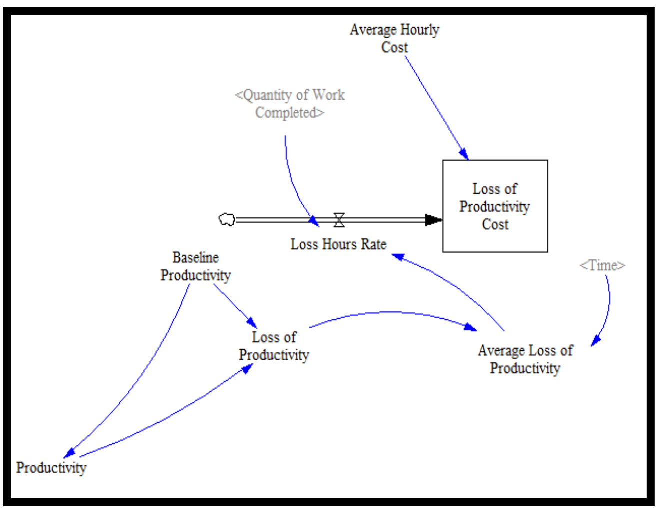


Figure 6-11. Cumulative Cost of Loss of Productivity.

6.6.5 Management Disruptions Feedback Loops

It is well known among construction industry practitioners and academia that any kind of disruptions may affect labor productivity but quantifying the impact of disruption is extremely difficult. Little research is available on quantifying the impact of delays, interruptions, and disruptions on labor productivity based on empirical data. Disruption Index (DI) introduced in 1995 by Thomas and Oloufa is a measure of the extent to which a project was disrupted. It is calculated using Equation 6.30:

$$\text{MDI} = \frac{Number\ of\ Disruption\ Days}{Total\ Number\ of\ Days} * 100 \qquad Equation\ 6.30$$

Based on Thomas and Oloufa's study, the following curve was developed which shows the decline in Performance Factor (PF) as DI increase (Figure 6.12). PF was calculated as follows (Equation 6.31):

$$PF = \frac{Baseline\ Productivity}{Actual\ Productivity} \qquad Equation\ 6.31$$

Thomas and Oloufa's study looked at the ripple effect of disruptions. The ripple effect of disruptions is considered as a situation where disruptions effects are rigorous and the impact of those affects the work outside the disrupted area. The ripple effect of disruptions was quantified using the following equation (Equation 6.32):

$$PF = 1.19 - 0.94(MDI)^{1.05} \qquad Equation\ 6.32$$

The ripple effect of disruption was included in the developed SD model as shown in Figure 6.12.

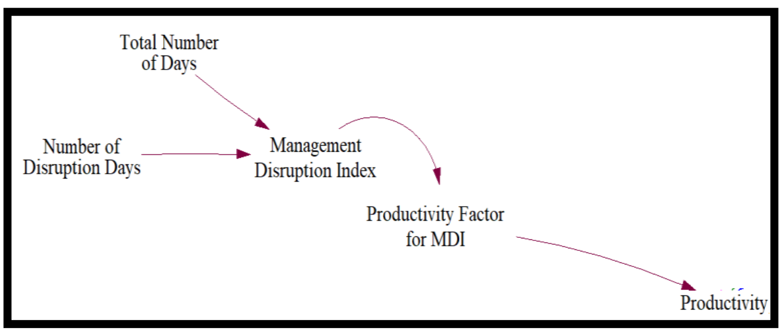


Figure 6-12. Impact of MDI on Productivity.

In this research, the number of disruption days was considered as the number of days the project experienced changes, overtime, shiftwork, and acceleration. Equation 6.33 was modified to include new factors included in the developed SD model as follows (Figure 6.13):

$$\begin{aligned} Productivity = {} & Baseline\ Productivity * (1 + Effect\ of\ Temperature\ and\ Humidity \\ & + Learning\ Curve\ Effect + Overmanning + Overtime\ Effect\ on\ Productivity \\ & + Trade\ Stacking + Effect\ of\ Change\ Orders\ on\ Productivity \\ & + Productivity\ Factor\ for\ MDI\ ) \qquad Equation\ 6.33 \end{aligned}$$

6.7 Model Calibration

Prior to using the model to simulate the dynamics of various scenarios, the model was calibrated with data from the real case study. The data used for calibration was a 48500.027m^2 formwork installation with the planned duration close to seven years or 350 weeks and planned productivity of 25 hours per square meter. This means the job required around 1.2 million hours to be completed. “Work Perceived to Be Accomplished” included changes and rework. Table 6.7 shows the settings of the developed model variables which were considered as the baseline model. Figure 6.14 demonstrates the outcome of the simulations, the S-curve of the baseline model. The “Remaining Work to Be Done” started with the “Initial Quantity of Work” value of 1,200,000 hours required for installation of 48500.027m^2 over 350 weeks. Figure 6.15 shows the “Quantity of Work Completed” which increased from its initial value of 0 to 1,200,000 hours.

Table 6-7. Baseline Model Values.

No.	Variable Name	Baseline Value
1	Baseline Productivity	25 Hours per M2
2	Baseline Quality	80%
3	Project Complexity	0.6
4	Initial Quantity of Work	1,200,000 Hour
5	Time for Disposition Approval	140 Hours
6	Average Time to Detect Defect	20 Hours
7	Mean Time to Approve Changes	140 Hours
8	Standard Workweek	70 Hours/Week
9	Actual Crew Size	22 Persons
10	Optimum Crew Size	18 Persons
11	Planned Manpower	85 Persons
12	Time to Hire	14 Days
13	Learning Curve	5% (Minor)
14	Mean Time to Gain Experience	30 Days
15	Turnover Factor	10%
16	Temperature	40F
17	Humidity	5%
18	Frequency of Changes	1%
19	Average Hourly Cost	120$/Hour

Figures 6.16 to 6.18 show the “Identified Changes”, “Approved Changes”, and “Completed Changes” generated by the baseline model. Figure 6.18 shows “Completed Changes” value for 104000 hours. Therefore, the “Percentage of Changes” generated in the baseline model was about 9%. Figure 6.19 shows how the “Work Perceived to Be Accomplished” increased from zero to 1,400,000 hours, which included “Initial Quantity of Work”, “Discovered Rework”, and “Completed Changes”.

It should be noted that “Work Perceived to Be Accomplished” was greater than “Initial Quantity of Work” as a result of several factors, including “NCR Generation Rate”, “Rework Discovery Rate”, and “Quality”. For showing the impact of “Quality” on the “NCR Generation Rate”, the “Baseline Quality” changed from 80 to 100%. Therefore, the “Remaining Work to Be Done” with perfect quality would take 267 weeks, 87 weeks earlier than the baseline case.

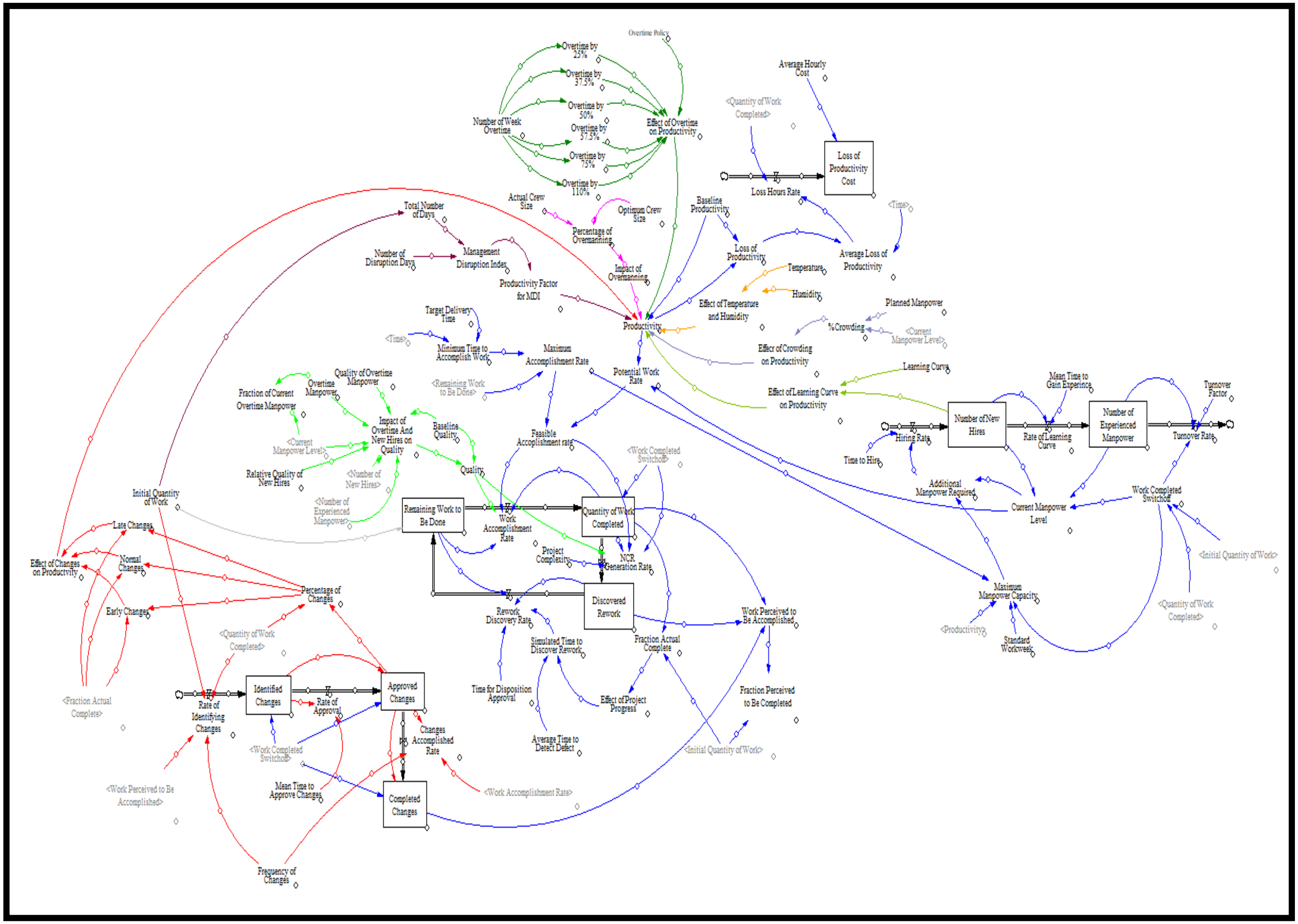


Figure 6-13. Complete Developed SD Model.

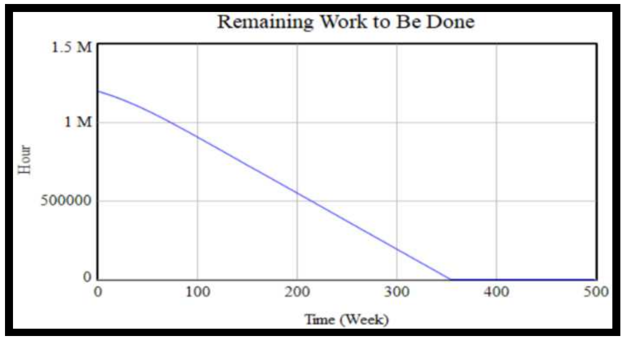


Figure 6-14. Remaining Work to Be Done.

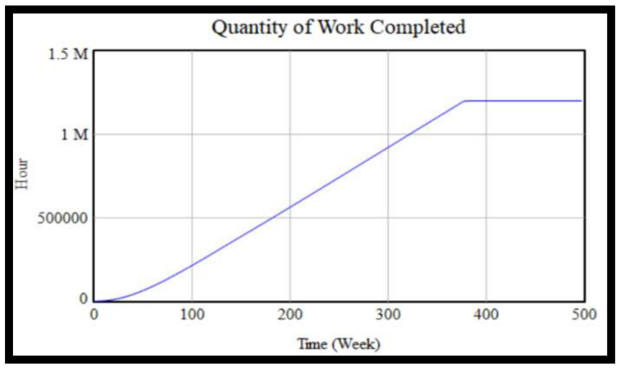


Figure 6-15. Quantity of Work Completed.

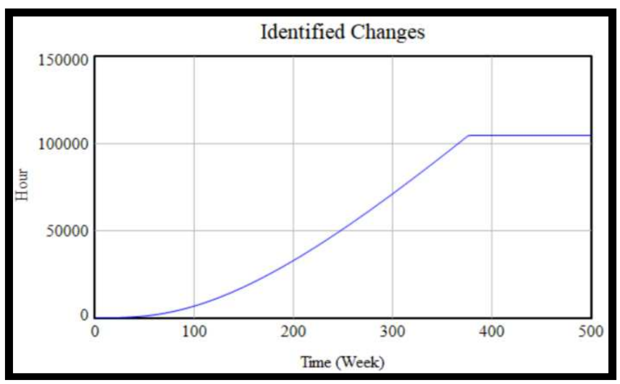


Figure 6-16. Identified Changes.

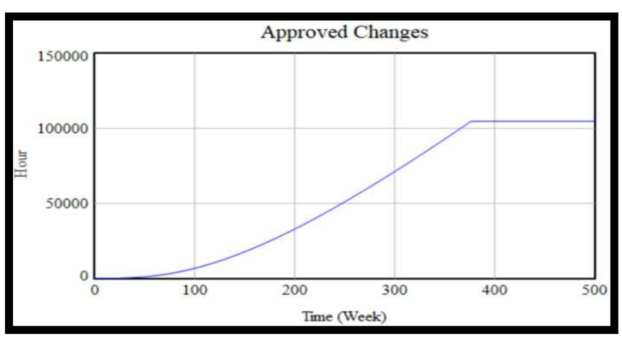


Figure 6-17. Approved Changes.

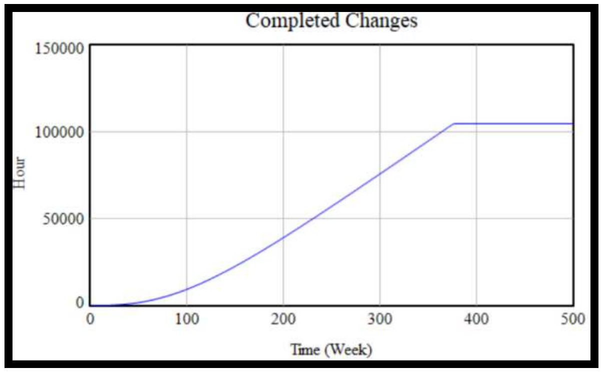


Figure 6-18. Complete Changes.

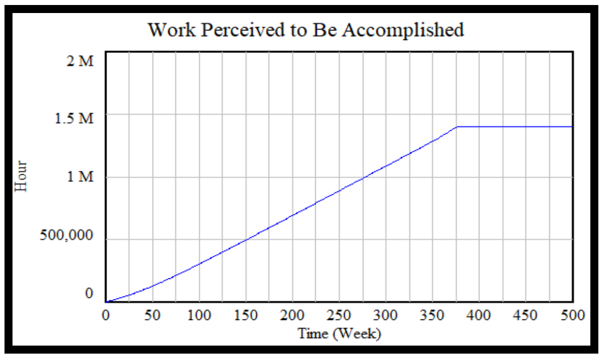


Figure 6-19. Work Perceived to Be Accomplished.

Figures 6.20 and 6.21 show the 87 weeks difference between the assumed “Perfect” and “Baseline” quality cases for “Quantity of Work Completed” and “Remaining Work to Be Done”. Figure 6.22 shows a comparison of the “Work Perceived to Be Accomplished” for the perfect quality and baseline quality cases. The figure shows that in the “Perfect Quality” case, “Work Perceived to Be Accomplished” was reduced by 100,000 hours which is the number of Completed Changes and Rework generated. This test was conducted to calibrate the developed model and show model robustness.

Figure 6-20. Baseline Quality vs. Perfect Quality.

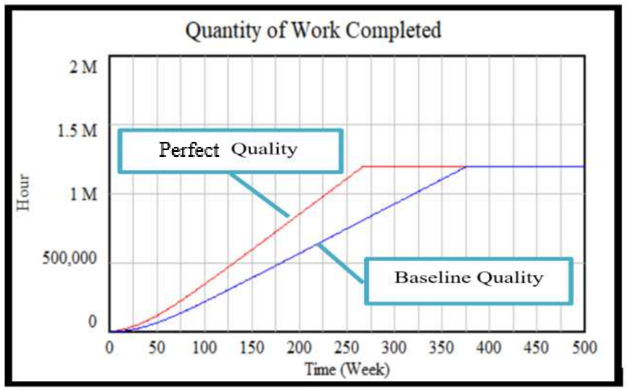


Figure 6-21. Quantity of Work Completed for Prefect and Baseline Quality.

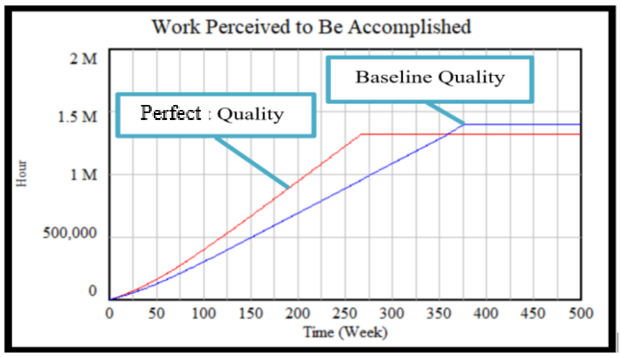


Figure 6-22. Work Perceived to Be Accomplished for Prefect and Baseline Quality.

6.8 Model Validation

Validation is the most important part of SD simulation modeling. Any simulation-based models cannot be approved unless the model has passed the tests of validation (Martis, 2006). Sargent and Balci (2017) state that "validation is concerned with whether the model adequately represents a system for the model's purpose". A model should be assessed for its usefulness rather than its absolute validity and rejecting a model because it fails to repeat a precise duplication of the past data is inadequate assessment. In other words, a model cannot have absolute validity, but it should be valid for the purpose for which it is developed (Martis, 2006). Validation does not exactly explain how a model can improve the relationship between the predicted results and the actual data. The essential purpose of validation includes identification of error and uncertainty in a qualitative model and quantification of numerical error in a quantitative model by comparing predicted results and actual data. SD validation means the validity of its configuration including the performance its casual loop as initial design. The validation process requires subjective and expert judgement. Validation for SDs should look at system behavior and focus on key time patterns rather than discrete data points (Barlas, 1996). The developed model was validated by comparing the predicted results against the project data regarding "Quantity of Work Completed" in the form of a physical percentage of complete. R-squared and adjusted R-squared were calculated using Equations 6.34 and 6.35 in order to compute the correlation between developed model output and project output:

$$R^2 = \frac{COVAR(PData, AData)}{STDEV\ (PData) * STDEV\ (AData)} \qquad \text{Equation 6.34}$$

Where PData is predicated data calculated by the developed model and Adata is actual data from the case study.

$$R^2_{Adj} = 1 - \frac{(1 - R^2)(n - 1)}{n - k - 1} \qquad \text{Equation 6.35}$$

Where n is the number of points in the dataset and k is the number of variables in the developed model. Figure 6.23 and Table 6.8 show the results of simulation including all the variables. As can be seen, the model can reproduce project data regarding "Quantity of Work Completed" with high accuracy. R^2 and adjusted R^2 for the developed model were 99.30 and 99.15%, respectively, the MAE 0.969 and MSE 0.02, and RMSE 0.14.

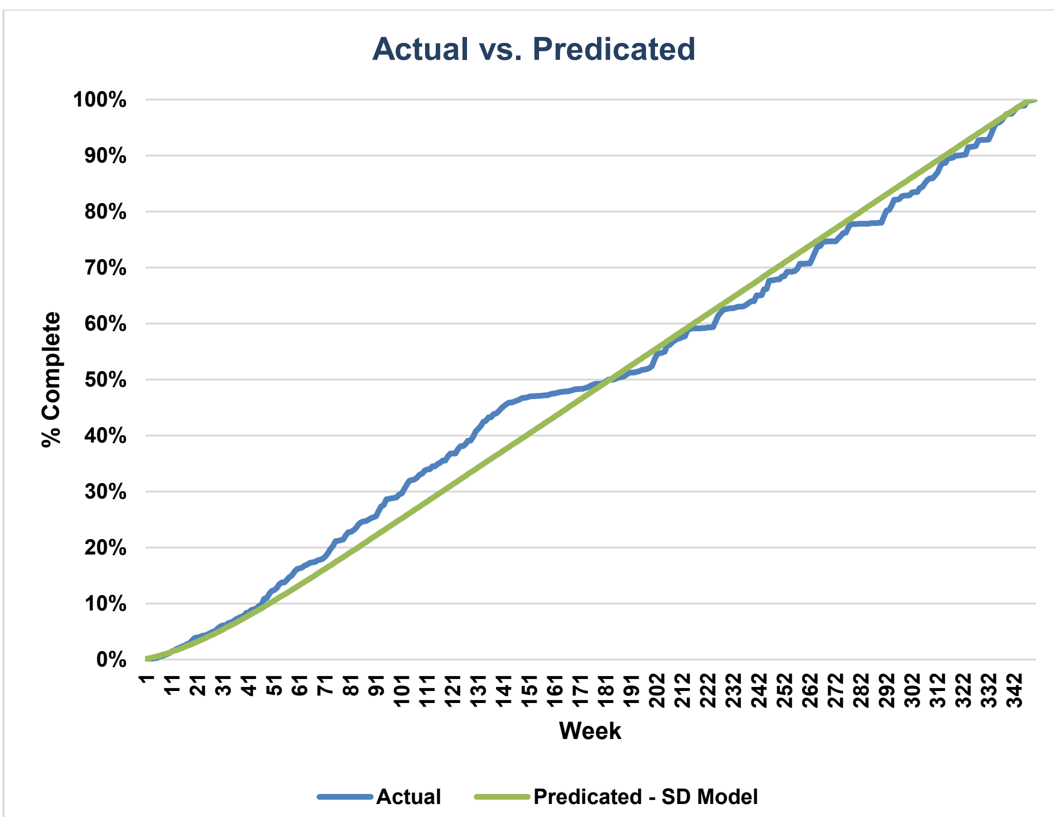


Figure 6-23. Validation Results of Baseline Model.

Table 6-8. Sample of Validation Data Set for Baseline Model.

Week	Actual		SD Model		Stat		
	% Complete	Cumulative	% Complete	Cumulative	Error	ABS	Squared Error
0	0.000%	0.000%	0.000%	0.000%	0.000%	0.000%	0.000000
1	0.061%	0.061%	0.160%	0.160%	-61.966%	61.966%	0.383973
2	0.035%	0.096%	0.098%	0.258%	-62.978%	62.978%	0.396617
3	0.015%	0.111%	0.105%	0.363%	-69.499%	69.499%	0.483005
4	0.114%	0.224%	0.112%	0.475%	-52.775%	52.775%	0.278517
5	0.097%	0.321%	0.118%	0.593%	-45.889%	45.889%	0.210580
6	0.291%	0.612%	0.125%	0.718%	-14.778%	14.778%	0.021839
7	0.011%	0.623%	0.131%	0.849%	-26.639%	26.639%	0.070966
8	0.191%	0.813%	0.137%	0.986%	-17.498%	17.498%	0.030617
9	0.170%	0.984%	0.143%	1.128%	-12.826%	12.826%	0.016450
10	0.209%	1.193%	0.148%	1.277%	-6.550%	6.550%	0.004290

6.9 Impact of Change Orders with Different Variables on Developed Model Behavior

Models should be tested for extreme conditions to check the robustness of the developed model. It is useful to understand the behavior of the developed model and how the model functions under all probable realistic states. The model should perform in an accurate and realistic manner no matter how intense the inputs forced on the developed model may be (Sterman, 2000).

The amount of change orders on productivity was considered between 6 to 10% and was combined with the other variable effects outlined in this section in order to study model behavior. After calibrating the developed model, the model was used to study the impact of different variables on the developed model under extreme conditions. In this test, different values were given to the selected models' variables and the generated behavior compared with the behavior of a real system. As an example of extreme conditions, the model was run by assuming 40% overmanning along with the entire simulation. The model behavior was compared to the real system, as shown in Figure 6.22. The developed stock-flow diagrams of the previous sections were based on expert knowledge, previous literature, and the person experienced gained from over fifteen years working on several mega projects. The values assumed for the variables of the model were based on existing project information and existing knowledge found in the literature.

6.9.1 Impact of Quality on the Developed Model

In this section, the impacts of Quality on NCR generation, "Discovered Rework", and the consequent impacts on productivity were tested by simulating the model for 60, 70, and 80% (baseline) values of "Quality". Figure 6.24 shows the impact of Quality on "Remaining of Work to Be Done" for three different values of "Baseline Quality". S-curves shows the decrease rates of “Remaining of Work to Be Done” as work progress. Thus, Figure 6.24 shows that the decrease rates of “Remaining of Work to Be Done” for 80% Quality were the highest and 60% the lowest. A 60 and 70% values for Quality led to needing more time to deliver the project. 582 weeks were needed for 60% Quality and 435 weeks for 70% Quality. Figure 6.25 shows the “Identified Changes” generated at three Quality levels. It can be seen from the Figure 6.25 that 60% generates the highest “Identified Changes” about 142,000 hours, followed by 70% Quality with 116,000 hours, while 80% Quality generated the lowest changes at 104,000 hours.

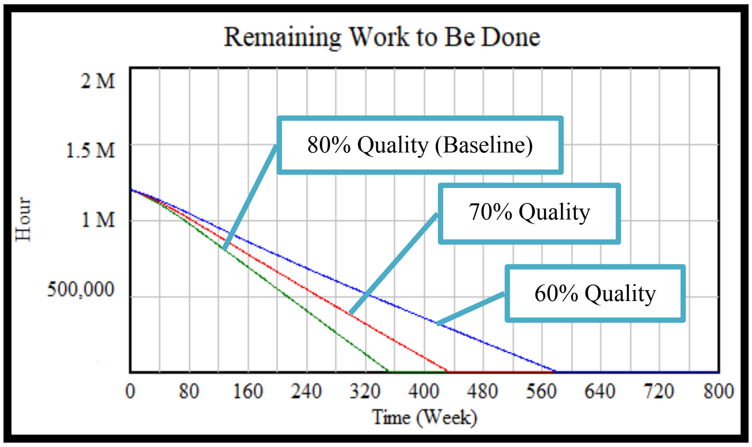


Figure 6-24. Impact of Quality on Remaining Work to Be Done.

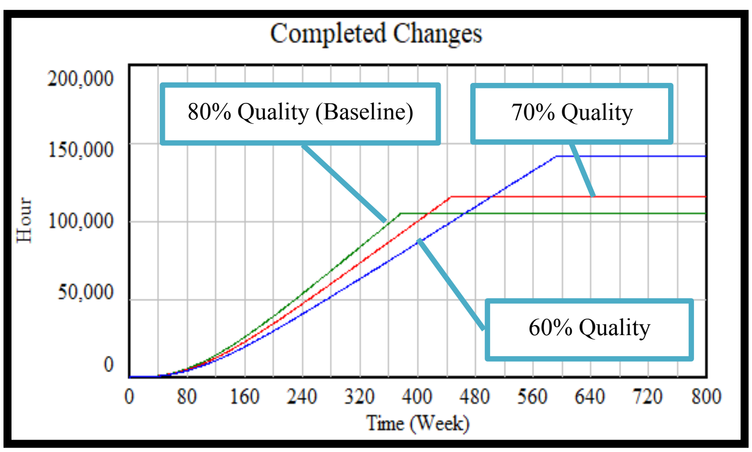


Figure 6-25. Impact of Quality on Identified Changes.

Figure 6.26 shows the “Productivity” values for the three Quality cases. It can be seen from Figure 6.26 that a Quality of 60% generates the highest “Productivity”, followed by

70%, while 80% generates the lowest “Productivity” value. For a 60% Quality value, the productivity value will reach the maximum of 34 hrs./m^2 and loss of productivity occurring during three cases.

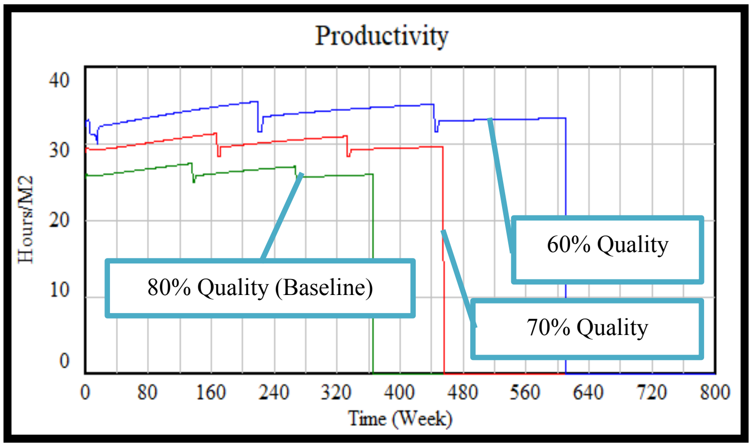


Figure 6-26. Impact of Quality on Productivity.

Table 6.9 shows the maximum and minimum productivity value for three different cases.

Table 6-9. Productivity Values for Different Quality Values.

	Productivity (Hrs/M2)		
Quality Value	**Maximum**	**Minimum**	**Average**
60%	35.5	29.8	33.18
70%	31.3	28.3	30.0
80%	27.4	25.0	26.3

Figure 6.27 shows “Loss of Productivity” caused by a Quality of 60 and 70%. Sixty percent of Quality shows project productivity is influenced more severely than with 70%. Table 6.9 shows the maximum, minimum, and average loss of productivity value.

Table 6-10. Loss of Productivity Values for Different Quality Values.

Loss of Productivity			
Quality Value	**Maximum**	**Minimum**	**Average**
60%	42%	19%	35%
70%	25%	13%	20%
80%	10%	0%	5%

It can be seen from Table 6.10 that 60% Quality generates a maximum loss of productivity value of 35% on average, followed 70% Quality with 20% loss of productivity. In addition, the project experienced 5% loss of productivity. The cumulative costs of the loss of productivity associated with three cases of Quality are shown in

Figure 6.28. Table 6.11 demonstrates the cumulative cost of for a 60, 70, and 80% Quality.

Table 6-11. Loss of Productivity Cumulative Labor Cost for Three Quality Cases.

Quality	Cumulative Labor Cost
60%	CAD 14,610,000
70%	CAD 4,580,000
80%	CAD 336,500

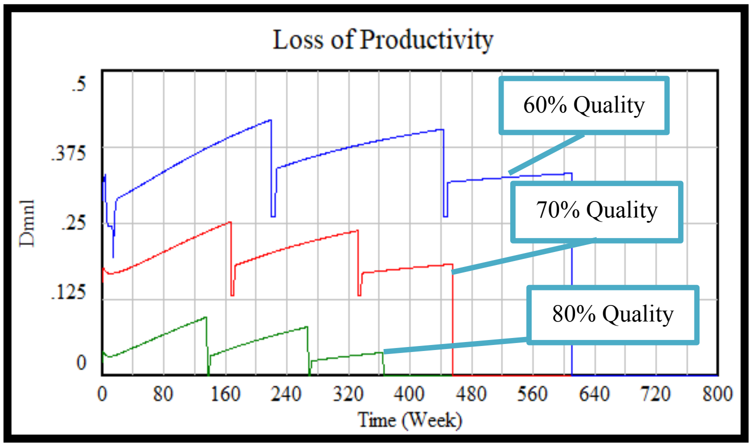


Figure 6-27. Loss of Productivity Caused by Different Quality Values.

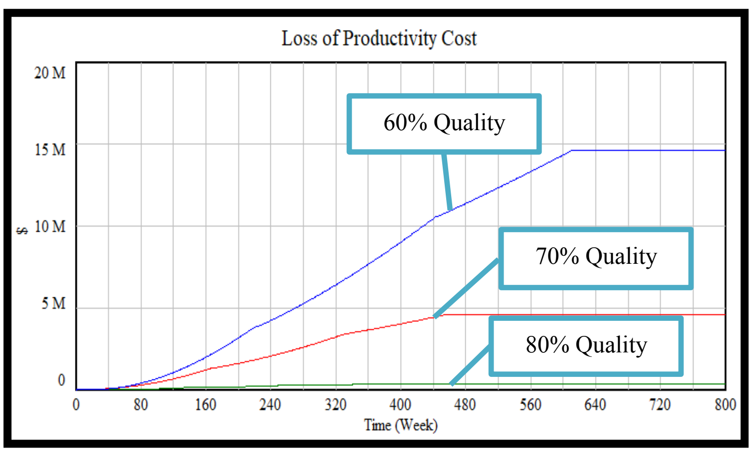


Figure 6-28. Cumulative Loss of Productivity of Cost for Three Quality Cases.

6.9.2 Impact of Overmanning on the Developed Model

In this section, the impact of “Percentage of Overmanning” was considered for the developed model’s major variables by simulating the model for different values of “Overmanning”. Values for “Percentage of Overmanning” of 10, 20, and 30% were considered. Figures 6.29 and 6.30 show “Productivity” and “Loss of Productivity “ and

"Loss of Productivity Cost" for the three different cases, as shown in Table 6.12. Figure 6.29 shows "Productivity" for "Percentage of Overmanning" at 10, 20, and 40%.

Table 6-12. Three Different Scenarios for "Percentage of Overmanning".

	Case 1	Case 2	Case 3
Actual Crew Size	20	22	26
Optimum Crew Size	18	18	18
Percentage of Overmanning	~10%	~20%	~40%

A look at the curve for 10% of overmanning (green line) shows fewer increases than 20% (red line) and 40% (blue line). In addition, the project experienced delays due to loss of productivity as can be seen in Figure 6.30. Table 6.13 summarizes the productivity achieved under the three "Percentage of Overmanning" cases.

Table 6-13. Productivity Value for Different Percentage of Overmanning.

	Productivity (hrs./M2)		
Percentage of Overmanning	**Maximum**	**Minimum**	**Average**
10%	27.74	25.31	26.61
20%	28.32	25.82	27.17
40%	29.13	26.51	27.96

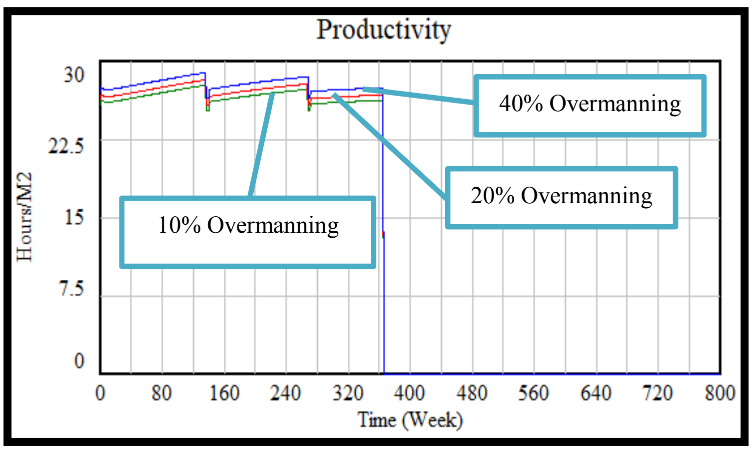


Figure 6-29. Impact of Overmanning on Productivity.

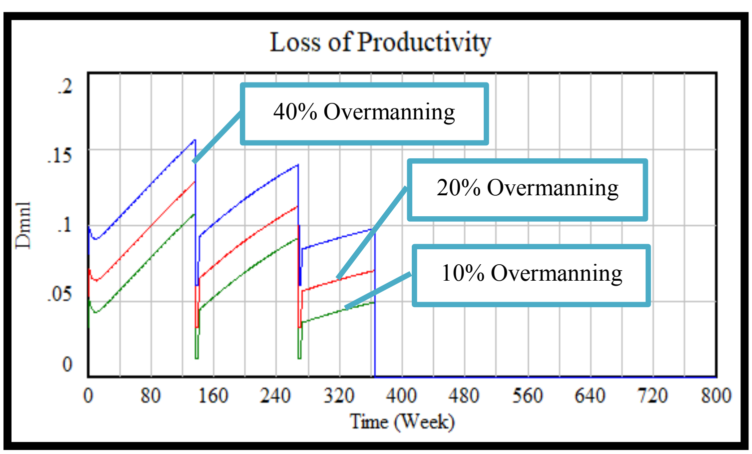


Figure 6-30. Loss of Productivity Due to Overmanning.

Figure 6.30 shows “Loss of Productivity” due to Overmanning. Based on the achieved productivity, “Loss of Productivity” reached 6, 9, and 12% under 10, 20, and 40 “Percentage of Overmanning” percentages, respectively (Table 6.14).

Table 6-14. Loss of Productivity for Different Percentage of Overmanning.

	Loss of Productivity		
Percentage of Overmanning	**Maximum**	**Minimum**	**Average**
10%	11%	1%	6%
20%	13%	3%	9%
40%	16%	6%	12%

Figure 6.31 shows the impact of the cumulative loss of productivity cost for three cases of Overmanning. The cumulative loss of productivity cost for 10% Overmanning (green line) was CAD 492,200 dollars and increased to CAD 834,400 dollars for 20% (red line). Forty percent Overmanning increased the loss of productivity cost to CAD 1,438,000 dollars (blue line).

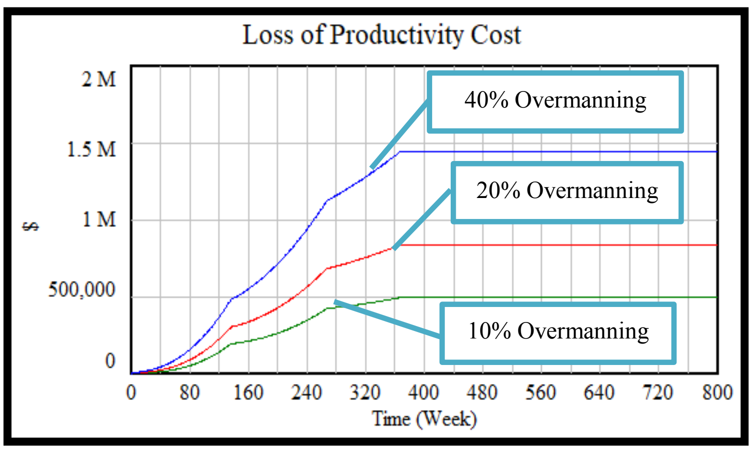


Figure 6-31. Cumulative Loss of Productivity Cost for Three Overmanning Cases.

6.9.3 Impact of Temperature and Humidity on the Developed Model

In this section, the impact of Temperature and Humidity for three different cases were analyzed to study the behavior of the developed model. Humidity value for three cases was assumed to be 85% for the convenience of simulation. Table 6.15 shows the Temperature values for different cases.

Table 6-15. Three Different Cases for Temperature and Humidity.

	Case 1	**Case 2**	**Case 3**
Temperature (ºF)	70º	80	90
Humidity	85%	85%	85%

Figure 6.32 shows the “Effect of Temperature and Humidity” on “Productivity”. A look at the graphs demonstrates that “Productivity” declines as “Temperature” rise. It should be noted that “Humidity” plays a major role when combined with very high or very low temperatures. Table 6.16 shows Productivity values at a variety of relative Temperature and Humidity rates. It can be seen that the Productivity value doubled for 120ºF temperature and 85% Humidity. Table 6.17 and Figure 6.33 show Loss of Productivity for three different Temperature and Humidity cases.

Table 6-16. Productivity Value for Different Temperature and Humidity.

	Productivity (Hrs./M²)		
Percentage of Overmanning	**Maximum**	**Minimum**	**Average**
Case 1 (70ºF,85%H)	27.38	25.00	26.26
Case 2 (80ºF,85%H)	28.63	26.25	27.51
Case 3 (90ºF,85%H)	31.89	29.50	30.76

Table 6-17. Loss of Productivity due to Temperature and Humidity.

Loss of Productivity			
Percentage of Overmanning	**Maximum**	**Minimum**	**Average**
Case 1 (70ºF,85%H)	10%	0%	5%
Case 2 (80ºF,85%H)	15%	5%	10%
Case 3 (90ºF,85%H)	28%	18%	23%

Figures 6.33 shows loss of productivity and Figure 6.34 displays the Cumulative Loss of Productivity cost for three cases of Temperature and Humidity. The Cumulative Loss of Productivity costs for 70ºF (green curve) were CAD 336,500 dollars and increased to CAD 1,187,000 dollars CAD for 80ºF (red curve). 80ºF shows that the loss of productivity cost was CAD 6,033,000 dollars (blue curve).

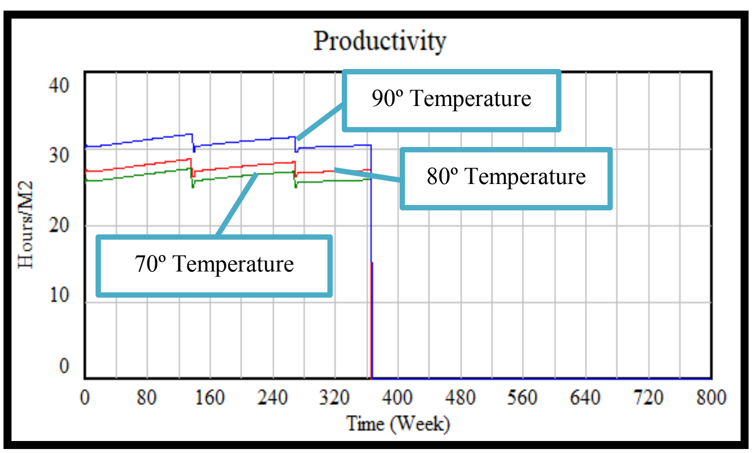


Figure 6-32. Impact of Temperature and Humidity on Productivity.

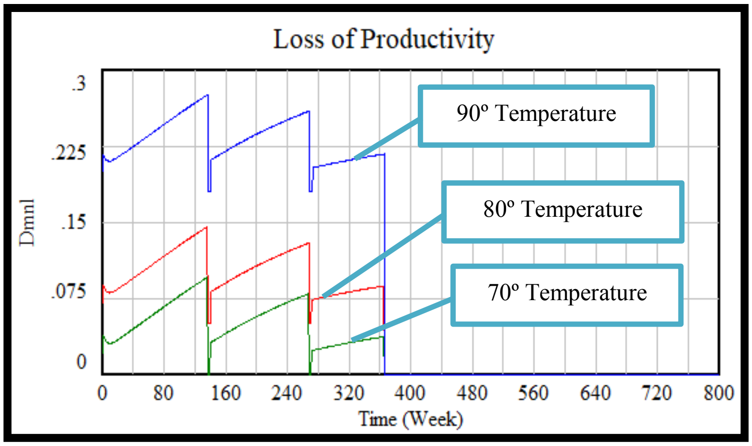


Figure 6-33. Loss of Productivity Due to Temperature and Humidity.

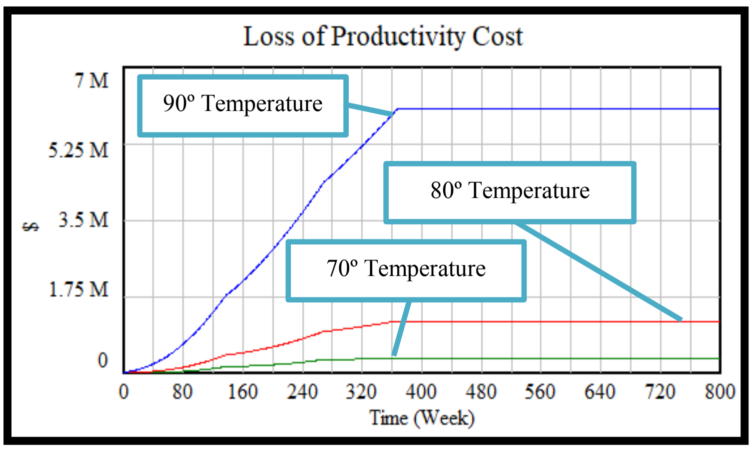


Figure 6-34. Cumulative Loss of Productivity Cost for Temperature and Humidity Cases.

6.9.4 Impact of Learning Curve on the Developed Model

In this section, the “Effect of Learning Curve on Productivity” was analyzed using three different cases as indicated in Section 6.4. The negative effect of the learning curve was considered and the value of inefficiency considered based the complexity of the job as follows (MCAA, 1994): 1) Case 1: Minor Learning Curve Effect; 2) Case 2: Average Learning Curve Effect; and 3) Case 3: Severe Learning Curve Effect. Figure 6.35 shows achieved productivity under different cases of the learning curve. Under minor learning effect, productivity (green curve) had the following values: 1) Maximum: 28.63 Hrs./M^2 – 15% Loss of Productivity; 2) Minimum: 26.25 Hrs./M^2 – 5% Loss of Productivity; and 3) Average: 27.51 Hrs./M^2 – 10% Loss of Productivity. The red curve in Figure 6.35 shows achieved productivity under average learning curve effect. The following value was extracted for average learning curve effect: 1) Maximum: 31.14 Hrs./M^2 – 25% Loss of Productivity; 2) Minimum: 28.75 Hrs./M^2 – 15% Loss of Productivity; and 3) Average:

30.01 Hrs./M^2 – 20% Loss of Productivity. The blue curve in Figure 6.35 represents productivity under Severe Learning Curve Effect. Under Severe Learning Effect, productivity followed these values:1) Maximum: 34.89 Hrs./M^2 – 40% Loss of Productivity; 2) Minimum: 32.50 Hrs./M^2 – 30% Loss of Productivity; and 3) Average: 33.76 Hrs./M^2 – 35% Loss of Productivity. Figures 6.36 shows Loss of Productivity and Figure 6.37 show Loss of Productivity Cumulative Cost for three different learning curve cases. The Cumulative Loss of Productivity Cost for minor learning curve effect (green curve) was CAD 1,137,000 dollars and increased CAD 4,570,000 dollars for the average learning curve effect (red curve). Severe learning curve effect Loss of Productivity Cost was CAD 13,880,000 dollars (blue curve).

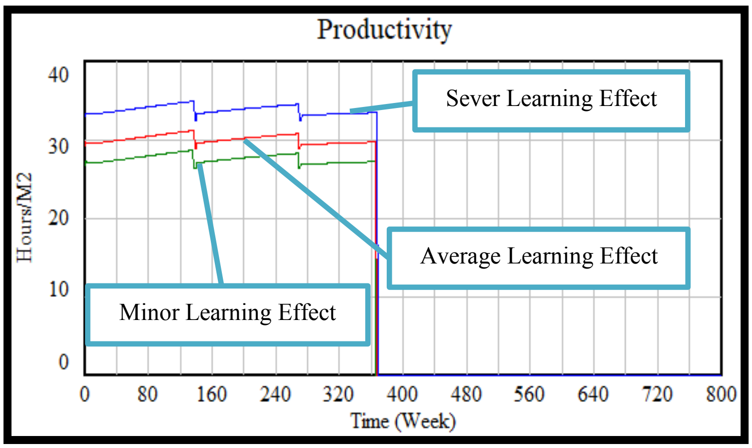


Figure 6-35. Impact of Learning Curve on Productivity.

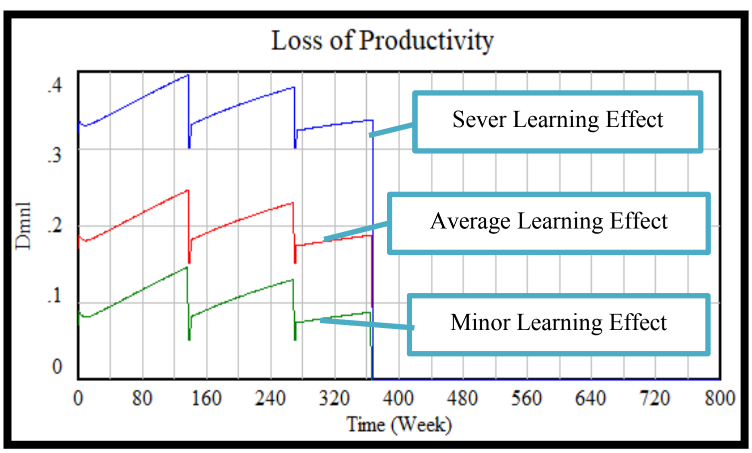


Figure 6-36. Loss of Productivity Due to Learning Curve.

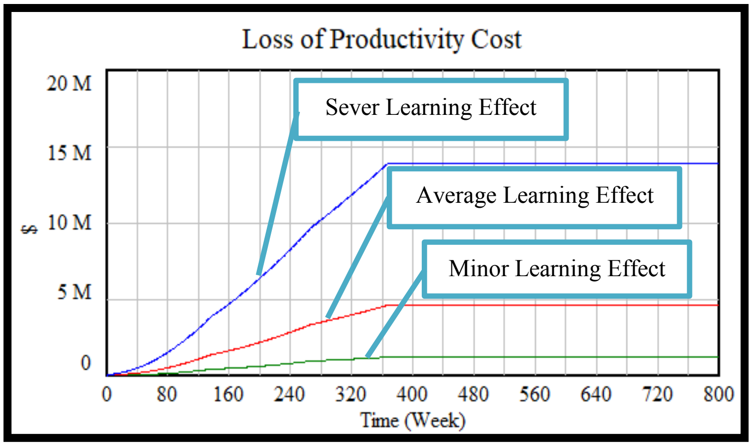


Figure 6-37. Cumulative Loss of Productivity Cost for Learning Curve.

6.9.5 Impact of Crowding on the Developed Model

As mentioned previously, crowing can affect productivity negatively. Three different scenarios were considered in this section as follows: 10, 20, and 40%of Crowding. Figure 6.38 shows the productivity pattern under three different scenarios. The green curve shows productivity reached under 10% of Crowding scenario as 27.03 Hrs./M^2 on average. Under 20% of Crowding (red curve), productivity reached 29.29, 26.88, and 28.16 Hrs./M^2 for maximum, minimum, and average, respectively. The blue curve represents productivity under 40% of Crowding. Under this percentage, productivity reached as high as 31.66 Hrs./M^2, while 29.25 Hrs./M^2 as the lowest value reached (Table 6.18).

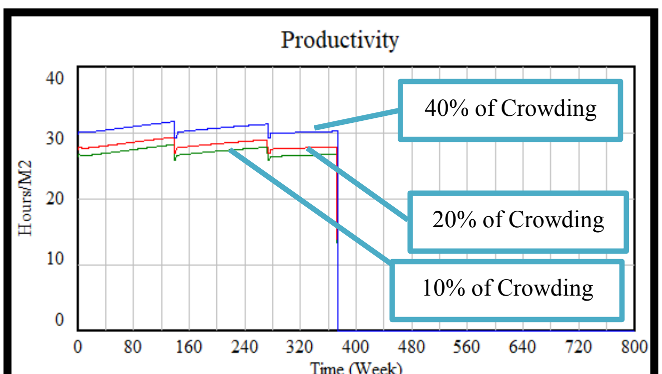


Figure 6-38. Impact of Crowding on Productivity

Table 6-18. Productivity Values for Different Crowding Cases.

	Productivity (Hrs./M^2)		
Percentage of Crowding	**Maximum**	**Minimum**	**Average**
10%	28.16	25.75	27.03
20%	29.29	26.88	28.16
40%	31.66	29.25	30.53

Figures 6.39 and 6.40 show Loss of Productivity and associated cumulative cost. Table 6.19 shows the Loss of Productivity values under three crowding scenarios. Ten percent of crowding results in 8% of Loss of Productivity on average with the Cumulative Cost of CAD 802,600 dollars, as shown in Figure 6.41 (green curve).

Table 6-19. Loss of Productivity due to Crowding.

Loss of Productivity			
Percentage of Crowding	**Maximum**	**Minimum**	**Average**
10%	13%	3%	8%
20%	17%	8%	13%
40%	27%	17%	22%

Twenty percent of crowding (red curve) led to 13% Loss of Productivity with a Cumulative Cost of CAD 1,864,000 dollars. A 22 percent Loss of Productivity (blue curve) was caused by 30% of Crowding with a Cumulative Cost of CAD 5,613,000 dollars. Table 6.20 summarize the Loss of Productivity Cumulative Cost.

Table 6-20. Loss of Productivity Cumulative Labor Cost for Three Crowding Cases.

Percentage of Crowding	Cumulative Labor Cost
10%	CAD 802,600
20%	CAD 1,864,000
40%	CAD 5,613,000

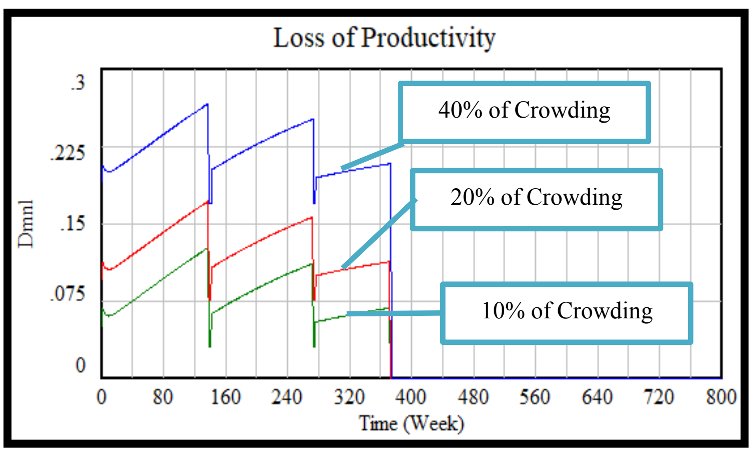


Figure 6-39. Loss of Productivity Due to Three Crowding Cases

6.9.6 Impact of Management Disruption on the Developed Model

In this section, the impact of management disruption will be analyzed for three different scenarios. Three scenarios were assumed as follows:

- Case 1: 20% of Management Disruption;
- Case 2: 30% of Management Disruption; and
- Case3: 40% of Management Disruption.

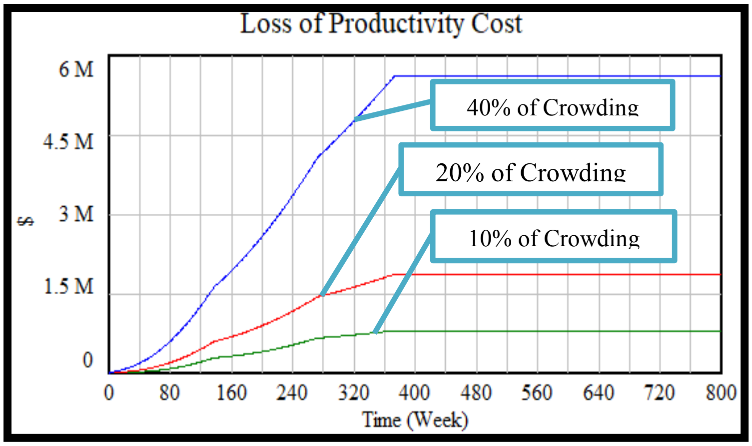


Figure 6-40. Cumulative Loss of Productivity Cost for Three Crowding Cases

Figure 6.41 demonstrates Productivity values under the three-abovementioned Management Disruption scenarios. The green curve shows the Productivity value under 20% of Management Disruption and red and blue curves shows productivity under 30 and 40%, respectively. Under 20% Management Disruption (green curve), the maximum productivity value was 27.00 Hrs./M^2.

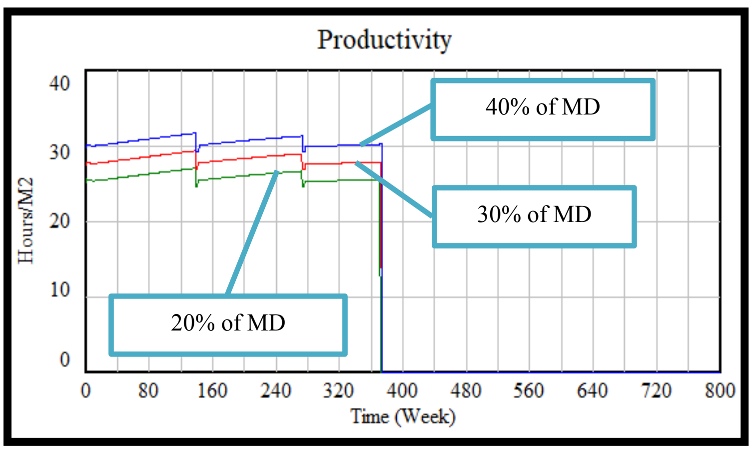


Figure 6-41. Impact of Management Disruption on Productivity.

24.59Hrs/M^2 was the minimum value and the average productivity was 25.87 Hrs./M2. The red curve represents Productivity under 30% Management Disruption. Productivity under this scenario reached a high of 29.30 Hrs./M2 and 29.25 Hrs./M2 was the lowest point, with 25.87 Hrs./M2 as the average (Table 6.21).

Table 6-21. Productivity Values for Different Management Disruption Cases.

	Productivity (Hrs./M^2)		
Management Disruption	**Maximum**	**Minimum**	**Average**
20%	27.00	24.59	25.87
30%	29.20	26.79	27.99
40%	31.44	29.13	30.28

Figures 6.42 and 6.43 show Loss of Productivity and associated Cumulative Cost. Table 6.22 displays the Loss of Productivity under three management disruption scenarios. Twenty percent of management disruption results in 8% Loss of Productivity on average with a Cumulative Cost of CAD 188,700 dollars, as shown in Figure 6.43 (green curve).

Table 6-22. Loss of Productivity due to Management Disruption.

Loss of Productivity			
Management Disruption	**Maximum**	**Minimum**	**Average**
20%	8%	0%	4%
30%	17%	8%	13%
40%	27%	17%	22%

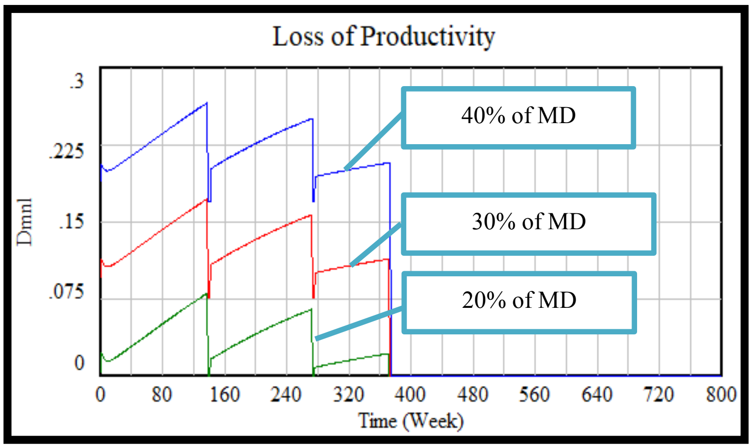


Figure 6-42. Loss of Productivity Due to Three Management Disruption Cases

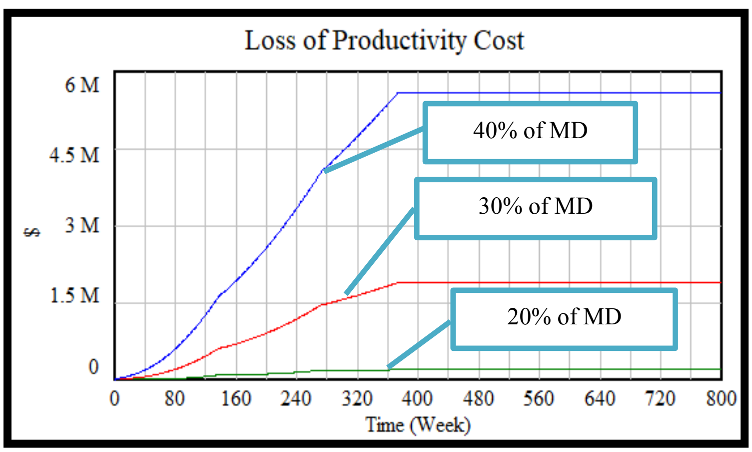


Figure 6-43. Cumulative Loss of Productivity Cost for Management Disruption

Thirty percent Management Disruption (red curve) led to 8% Loss of Productivity on average with Cumulative Cost of CAD 1,883,000 dollars. A 13% Loss of Productivity on average (blue curve) was caused by 40% Management Disruption with Cumulative Cost of CAD 5,579,000 dollars. Table 6.23 summarizes the Loss of Productivity Cumulative Cost.

Table 6-23. Loss of Productivity Cumulative Labor Cost for Management Disruption.

Management Disruption	Cumulative Labor Cost
20%	CAD 188,700
30%	CAD 1,883,000
40%	CAD 5,579,000

6.9.7 Impact of Overtime on the Developed Model

In this section, the impact of Overtime will be analyzed for three different scenarios. Three scenarios were assumed as follows:

- Case 1: 25% of Overtime;
- Case 2: 50% of Overtime; and
- Case3: 75% of Overtime.

Figure 6.44 demonstrates Productivity values under the three-abovementioned overtime scenarios. The green curve shows the Productivity value under 25% of Overtime Disruption and red and blue curves shows productivity under 50% and 75%, respectively. Under 25% Overtime (green curve), the maximum productivity value was 28.7 Hrs./M^2.

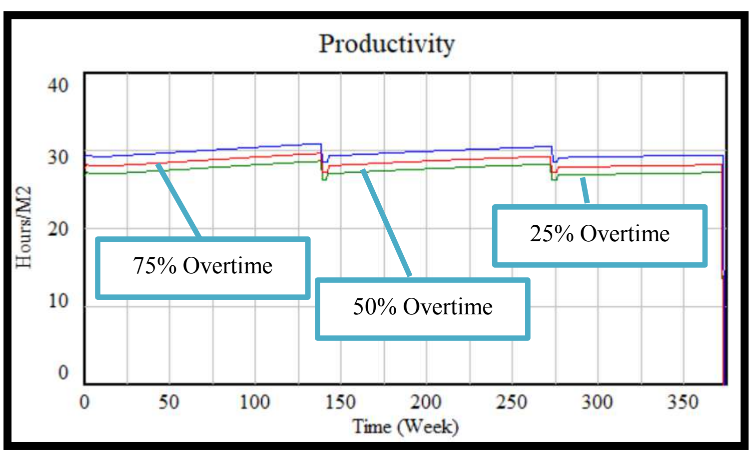


Figure 6-44. Impact of Overtime on Productivity.

26.30 Hrs/M^2 was the minimum value and the average productivity was 27.5 Hrs./M2. The red curve represents Productivity under 50% Overtime. Productivity under this scenario reached a high of 29.70 Hrs./M2 and 27.30 Hrs./M2 was the lowest point, with 28.50 Hrs./M2 as the average (Table 6.24).

Table 6-24. Productivity Values for Different Management Disruption Cases.

	Productivity (Hrs./M^2)		
Overtime	**Maximum**	**Minimum**	**Average**
25%	28.70	26.30	27.50
50%	29.70	27.30	28.50
75%	30.90	28.50	29.70

Figures 6.45 and 6.46 show Loss of Productivity and associated Cumulative Cost. Table 6.25 displays the Loss of Productivity under three overtime scenarios. Twenty five percent of overtime results in 10% Loss of Productivity on average with a Cumulative Cost of CAD 1,216,515 dollars, as shown in Figure 6.43 (green curve).

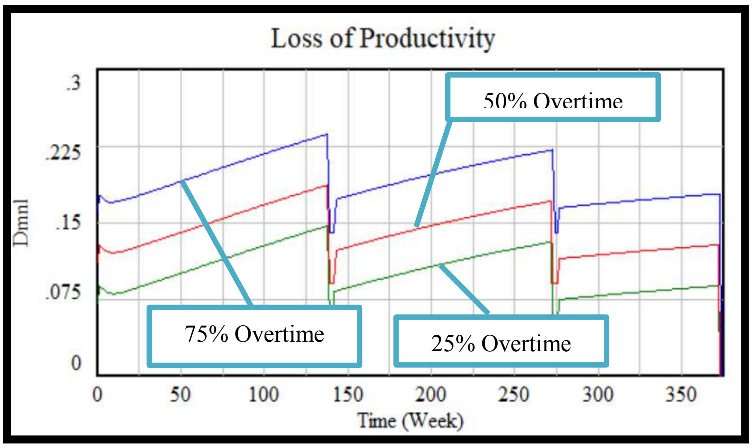


Figure 6-45. Loss of Productivity Due to Three Overtime Cases

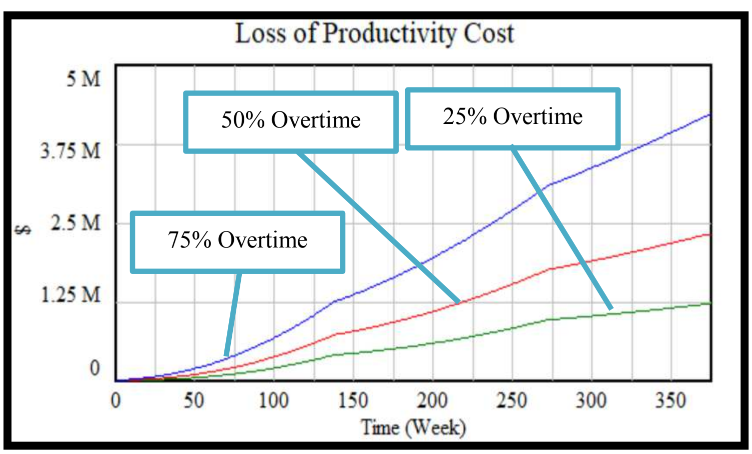


Figure 6-46. Cumulative Loss of Productivity Cost for Overtime

Table 6-244. Loss of Productivity due to Overtime.

Loss of Productivity			
Overtime	**Maximum**	**Minimum**	**Average**
25%	15%	5%	10%
50%	19%	9%	14%
75%	24%	14%	19%

Fifty percent overtime (red curve) led to 14% Loss of Productivity on average with Cumulative Cost of CAD 2,315,364 dollars. A 19% Loss of Productivity on average (blue curve) was caused by 19% Overtime with Cumulative Cost of CAD 4,206,175dollars. Table 6.26 summarize the Loss of Productivity Cumulative Cost.

Table 6-25. Loss of Productivity Cumulative Labor Cost for Overtime.

Overtime	Cumulative Labor Cost	
25%	CAD	1,216,515
50%	CAD	2,315,364
75%	CAD	4,206,175

6.10 Combined Impact of Different Variables on Developed Model

In the previous sections, the impact of different variables along with change orders was studied by simulating a model for different Management Disruption, Crowding, Learning Curve, Temperature and Humidity, Overmanning, and Quality values. In this section, the combined impact of these variables on the productivity of the developed model is investigated. Determining numerical values of the impact of combined variables can be carried out by varying any constant directly affected productivity. Therefore, sensitivity analysis is performed to understand the range of behavior of the developed model. The SD model was developed using Vensim software which uses the Monte Carlo simulation in performing sensitivity analysis. For this research, a sensitivity analysis was performed to assess the combined impact of Management Disruption, Crowding, Learning Curve, Temperature and Humidity, Overmanning, and Quality along with Change Orders. The model was run with all the constant variables set to baseline values, then the impact of the factors under consideration analyzed using Random Uniform Distribution (RUD). RUD, also known as a rectangular distribution, is a distribution that has constant probability (Figure 6.47).

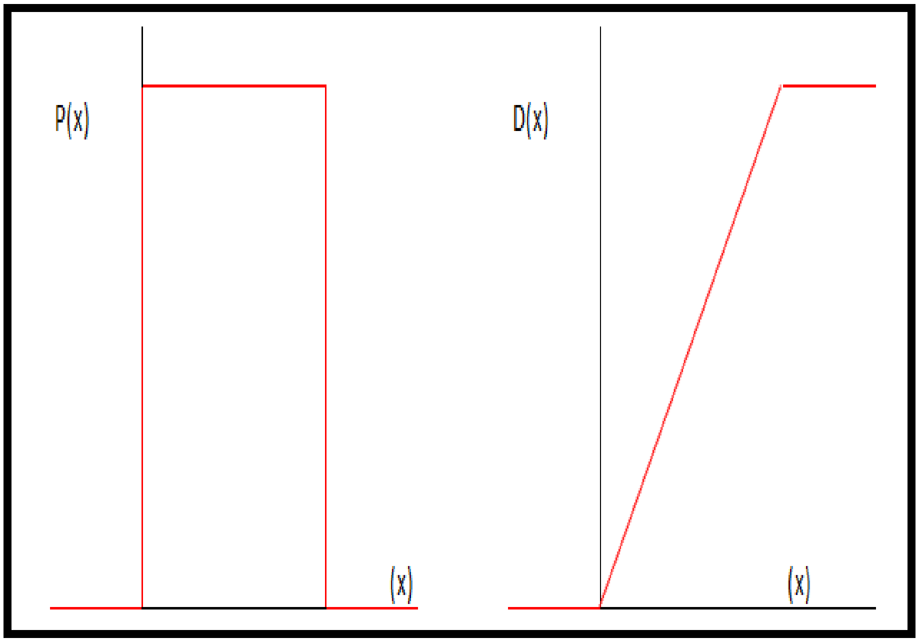


Figure 6-47. Probability Density Function and Cumulative Distribution Function.

The number of iterations was set to 100 for each sensitivity analysis run. The following combination of the above-mentioned variables was considered for the sensitivity analysis: Run 1 - Crowding and Management Disruption; Run 2 - Crowding and Learning Curve; Run 3 - Temperature and Humidity and Crowding; Run 4 - Temperature and Humidity and Leaning Curve; Run 5 - Overmanning and Crowding; Run 6 - Overmanning and Leaning Curve; Run 7 - Quality and Leaning Curve; and Run 8 - Crowding, Learning Curve, and Management Disruption.

Run – 1: Sensitivity analysis was performed to analyze the effect of crowding and management disruption using RUD for crowding rate from 0 to 50% as well as for management disruption. Figures 6.45 to 6.47 show the confidence boundaries for all potential output values of the variables including productivity, loss of productivity, and the cumulative loss of productivity cost, respectively. The sensitivity analysis results illustrate that the highest value for productivity was ~37 hrs./m2, which is a worst-case scenario and the lowest productivity was ~20 hrs./m2, as the best-case scenario, as well as the average productivity of ~27 hrs./m2 (Figure 6.48). For loss of productivity, the outer bounds of uncertainty (100%) show that the project experienced close to 45% loss of productivity and the average loss of productivity for this run was 25% (Figure 6.49). The cumulative loss of productivity cost for the worst-case reached ~ 21,000,000 dollars and the average cumulative loss of productivity cost was ~ 3,190,000 dollars (Figure 6.50).

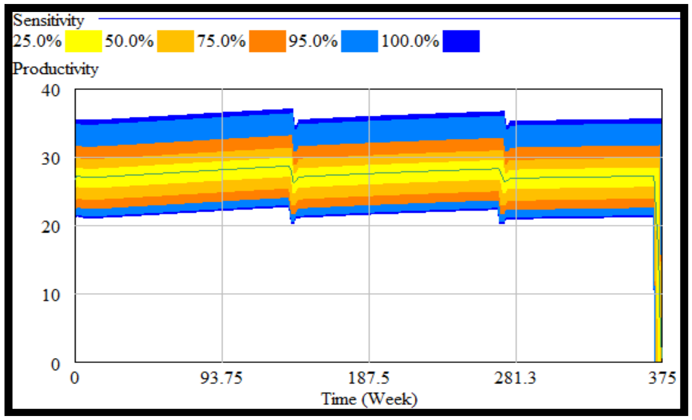


Figure 6-48. Run 1 - Productivity Sensitivity Analysis.

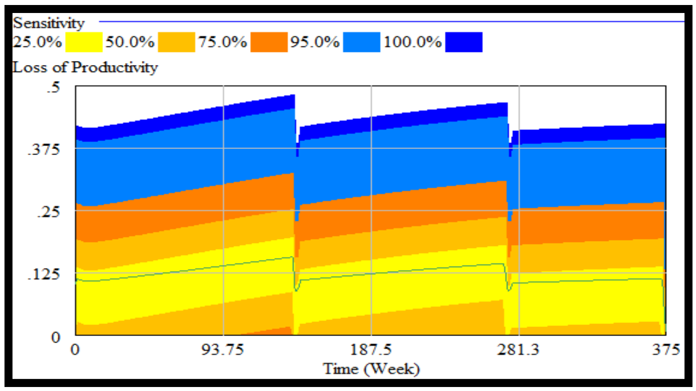


Figure 6-49. Run 1 - Loss of Productivity Sensitivity Analysis.

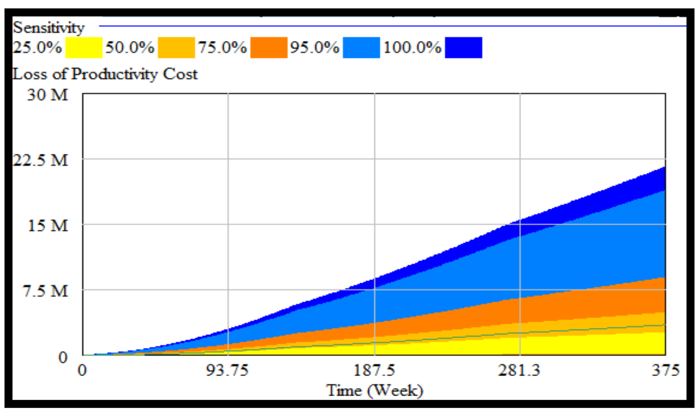


Figure 6-50. Run 1 - Cumulative Loss of Productivity Cost Sensitivity Analysis.

Since all the performed sensitivity analysis follows the same procedure, so the output values of the variables including productivity, loss of productivity, and the cumulative loss of productivity cost related to each Run (Run 2-8) are summarized in Table 6.27 and 6.28.

6.11 Summary

This chapter discussed modeling loss of productivity using SD by considering the effect of change orders and other contributing factors such as overtime, learning curve, overmanning, crowding, temperature and humidity, and quality on the loss of productivity. The developed SD model was calibrated and validated using a real data of mega structure, which is a massive concrete structure. The statistical performance indicators of the developed model shows acceptable values. After, the developed model was validated under an extreme values test for each contributing variable to loss of productivity. The extreme test reveals that Quality, Severe Learning Curve, and Temperature and Humidity are major contributors to Loss of Productivity followed by Crowding, Management Disruption, Average Learning Curve, Overmanning, and Minor Learning Curve (Figure 6.51). In the last step, a combination of contributing variables using sensitivity analysis function built-in Vensim software was examined.

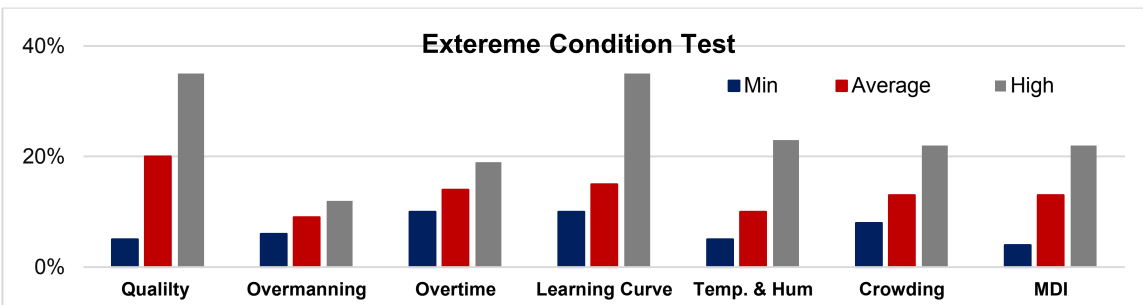


Figure 6-51. Maximum Value of Loss Productivity Generated Under Extreme Test.

Table 6-26. Sensitivity Analysis Summary (Run 1-4).

Run#		Run 1	Run 2	Run 3	Run 4
Description		Crowding (0%-50%) & Management Disruption (0%-50%)	Crowding (0%-50%) & Learning Curve (5%-30%)	Temperature (30ºF-120ºF) & Humidity (30%-80%) & Crowding (0%-50%)	Temperature (30ºF-120ºF) & Humidity (30%-80%) & Learning Curve (5%-30%)
Productivity	Max.	20 hrs./m^2	25 hrs./m^2	25 hrs./m^2	27 hrs./m^2
	Ave.	27 hrs./m^2	32 hrs./m^2	31.25 hrs./m^2	33.75 hrs./m^2
	Min	37 hrs./m^2	40 hrs./m^2	50 hrs./m^2	52 hrs./m^2
Loss of Productivity	Max.	45%	55%	95%	95%
	Ave.	25%	32%	26%	35%
Cumulative Loss of Productivity Cost	Max.	21,000,000 CAD	30,000,000 CAD	100,000,000 CAD	100,000,000 CAD
	Ave.	3,190,000 CAD	7,500,000 CAD	12,500,000 CAD	25,000,000 CAD

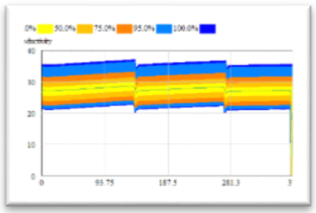
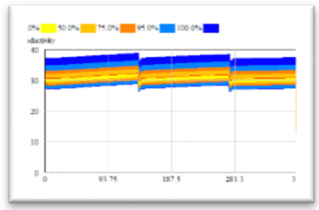
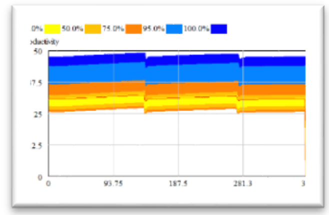
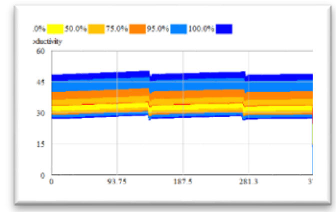
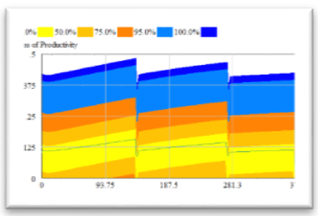
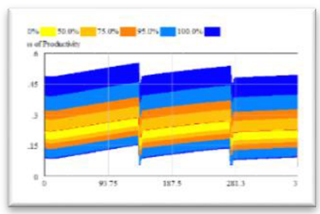
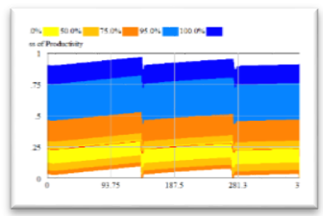
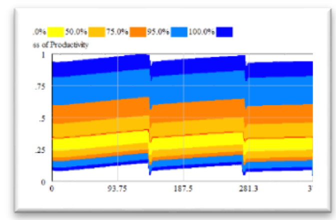
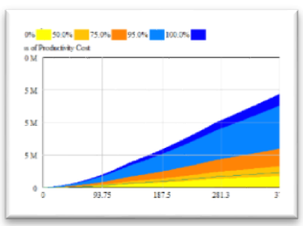
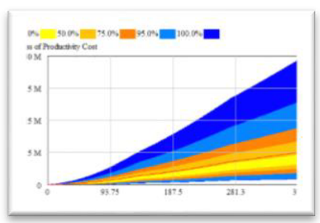
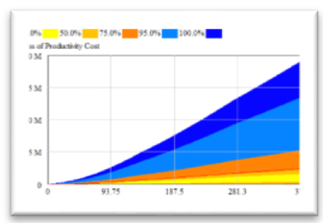
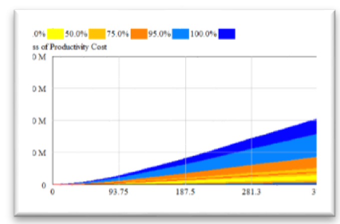
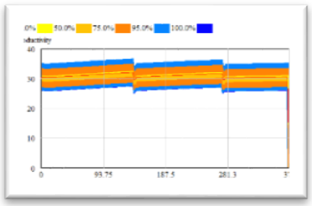
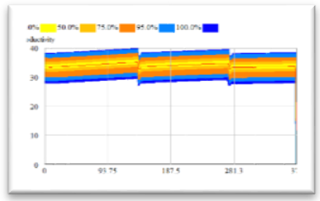
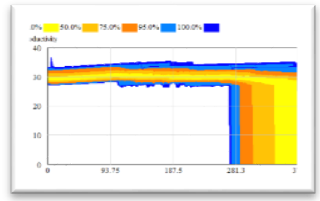
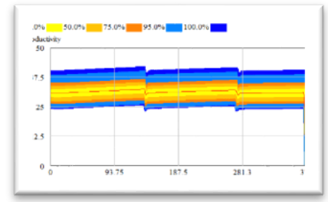
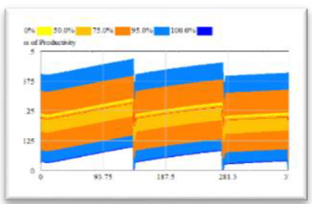
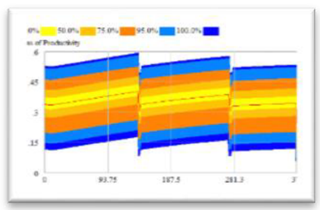
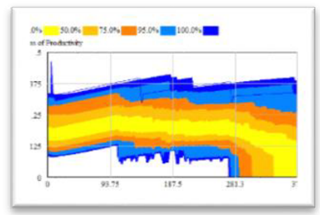
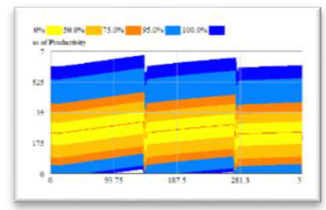
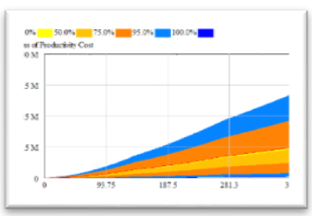
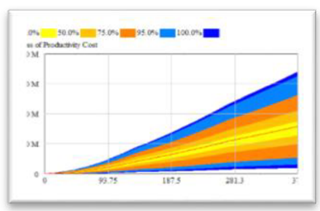
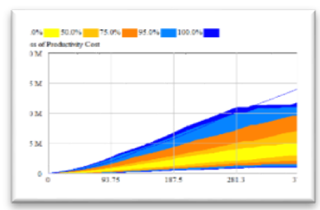
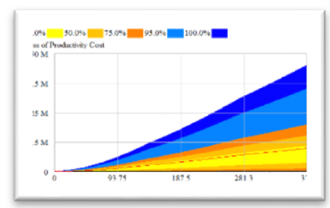
Run#	Run 1	Run 2	Run 3	Run 4
Figures	 Productivity	 Productivity	 Productivity	 Productivity
	 Loss of Productivity	 Loss of Productivity	 Loss of Productivity	 Loss of Productivity
	 Cumulative Loss of Productivity Cost	 Cumulative Loss of Productivity	 Cumulative Loss of Productivity	 Cumulative Loss of Productivity

Table 6-27. Sensitivity Analysis Summary (Run 4-8).

Run#		Run 5	Run 6	Run 7	Run 8
Description		Overmanning (0%-50%) & Crowding (0%-50%)	Overmanning (0%-50%) & Learning Curve (5%-30%)	Quality (0%-50%) & Learning Curve (5%-30%)	Crowding (0%-50%) & Learning Curve (5%-30%) & Management Disruption (0%-50%)
Productivity	Max.	25 hrs./m^2	35 hrs./m^2	28 hrs./m^2	24 hrs./m^2
	Ave.	31.25 hrs./m^2	36 hrs./m^2	33 hrs./m^2	31.25 hrs./m^2
	Min	35 hrs./m^2	40 hrs./m^2	35 hrs./m^2	40 hrs./m^2
Loss of Productivity	Max.	45%	60%	40%	69%
	Ave.	25%	35%	35%	33%
Cumulative Loss of Productivity Cost	Max.	22,000,000 CAD	35,000,000 CAD	14,000,000 CAD	43,000,000 CAD
	Ave.	7,500,000 CAD	15,000,000 CAD	6,000,000 CAD	10,000,000

Run#	Run 5	Run 6	Run 7	Run 8
Figures	 Productivity	 Productivity	 Productivity	 Productivity
	 Loss of Productivity	 Loss of Productivity	 Loss of Productivity	 Loss of Productivity
	 Cumulative Loss of Productivity Cost	 Cumulative Loss of Productivity	 Cumulative Loss of Productivity	 Cumulative Loss of Productivity

7. CHAPTER SEVEN: CASE STUDIES

7.1 General Overview

In order to validate the models developed and presented in Chapters 4, 5, and 6, a case study was selected and applied in this chapter. A case study involving a massive concrete structure in North America was selected and used to demonstrate the developed models' applicability. This chapter is divided into three main sections (Figure 7.1), in which data obtained from a concrete structure project is used to assess the FRCM model in the first section, labor productivity using PSO-RBFNN in the second section, and finally, SD modelling to quantitatively measure the impact of change orders on labor productivity in the last section. The results obtained from these methods were compared with the available actual data in order to illustrate the applicability of these models in the real world and conclusions extracted accordingly. Moreover, the models' outputs using the concrete structure case study were analyzed against statistical studies such as Ibbs and Leonard's model.

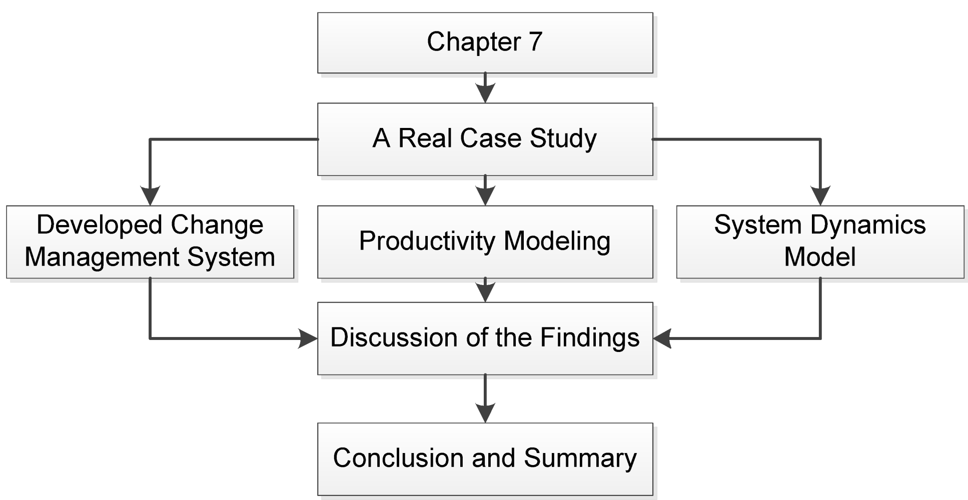


Figure 7-1. General Overview of Case Studies.

7.2 Change Management Case Study

A case study derived from a mega concrete infrastructure project in North America was used to assess the applicability of the developed model proposed in Chapter 4. The project name and parties involved in the project were kept confidential. The project was awarded to a prime contractor on or about November 2013 by the owner for the constructing related structures of the concrete infrastructure (Figure 7.2).

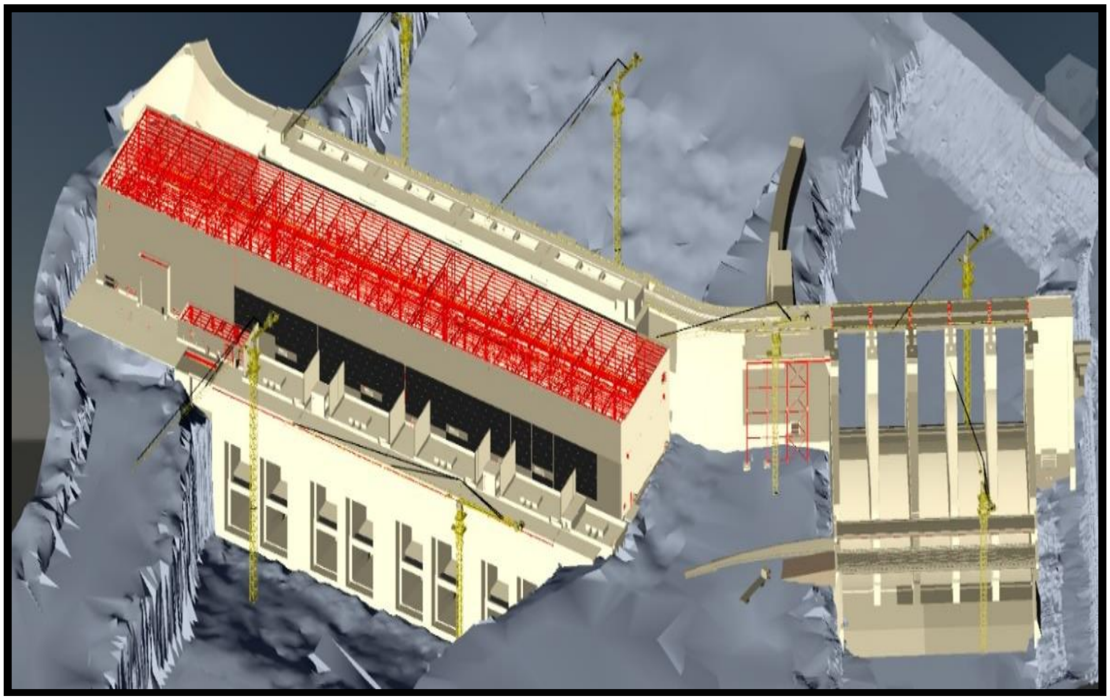


Figure 7-2. Concrete Infrastructure and Related Structures.

In this section, a major change is studied and how this change can be assessed using the FRCM developed in Chapter 4.

7.2.1. Joined Cover System Project Overview

The prime contractor proposed a change to their initial construction methods to carry out the concreting of the intake and powerhouse in a controlled environment by building a temporary shelter above the powerhouse area. Labeled the Cover System (CS), this temporary shelter was expected to be a crucial part of the construction methods and plan implemented by the prime contractor (Figure 7.3). The prime contractor awarded construction of the CS on December 2013 to a subcontractor with a stipulated subcontract price of CAD 17,666,401 dollars before taxes for procurement, fabrication, and erection of the CS steel structure, as well as the installation of the roof and wall cladding. To carry out the CS, the initial work schedule of the subcontractor was seven months, from March 2014 to September 2014, including the mobilization and demobilization periods. However, the contract was only signed by the involved parties in May 2014 due to design modifications by the prime contractor. The subcontractor submitted an updated work schedule reflecting the new dates for the erection of the steel structure from June 2014 to December 2014, duration less than seven months. The subcontractor started their work in July 2014. The late start of work was due to the delays in the finalization of foundations and site preparation by the prime contractor.

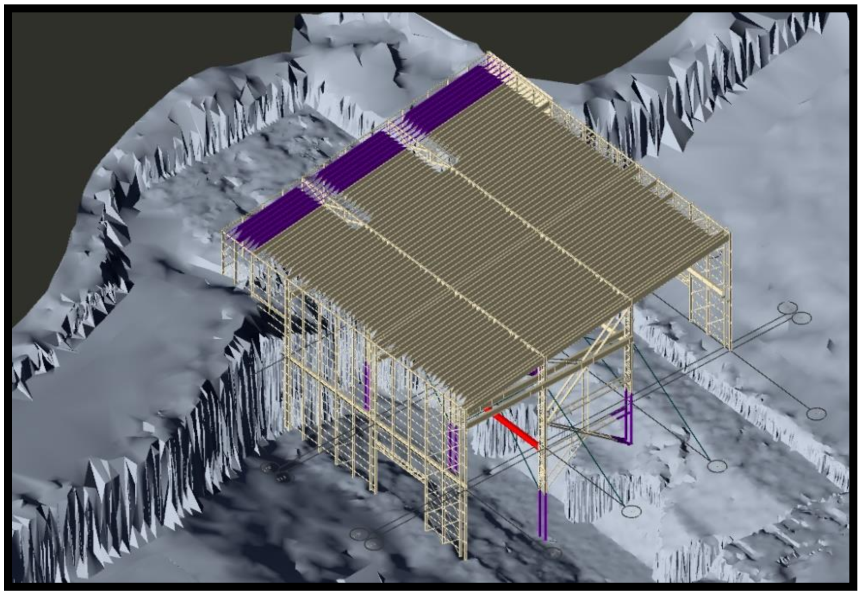


Figure 7-3. Schematic View of the CS Steel Structure.

The stipulated price contract was changed to a cost-plus contract as agreed by the involved CS project parties and the work agreed to be completed no later than March 2015, with a total of 110,000 direct hours and 15,000 supervision hours. It was also planned that half of CS, including an additional temporary exterior wall not part of the original scope of work would be finished no later than December 2014. However, since it appeared that this proposal was never agreed upon by all the parties, this resulted in an unsigned change order. The contractor terminated the contract by mid-December 2014 when it became clear that the construction of CS would result in an hours and cost overrun.

7.2.2. Integrated Cover System Execution Plan

Designed as a temporary heated shelter, CS was planned to allow the prime contractor a controlled environment to execute the construction of the powerhouse and intake year-around. Located above the future powerhouse, the CS was a steel structure rectangular building designed to house 18 overhead cranes for hoisting and handling of materials during the construction of the powerhouse. Divided into four units, as shown in Figure 7.4, the CS was designed to corresponding to the four generating units of the future powerhouse.

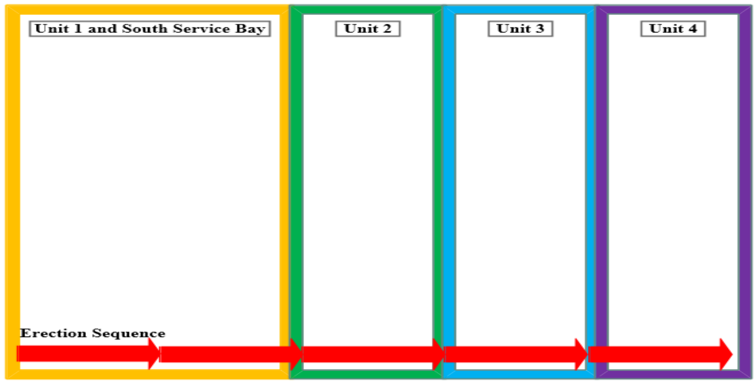


Figure 7-4. Erection Sequence of the CS.

The erection was planned by the subcontractor to take place close to one of the four tower cranes by Unit 1 and Service Bay (SB). The structural steel would be erected for each unit in numerical order. To start the process, enough concrete foundations and anchors needed to be completed by the prime contractor and handed over to the subcontractor. Figure 7.4 shows that each unit represents a construction schedule phase and that each work phase includes two different principal activities which were carried out by specific trades, structural steelwork, and insulation and cladding work. The structural steelwork mainly consisted of the erection of structural steel material such as columns, beams, trusses, struts, and vertical bracings as well as the erection of overhead cranes. These activities were planned to be carried out by ironworkers. The second main activity consisted of the installation of insulation and cladding on the roof and the walls of CS. The ironworkers were responsible for preassembling the roof and installing the roof deck. This activity was the prerequisite to the installation of the roof deck and to the insulation and cladding work (Figure 7.5).


Figure 7-5. Roof Deck Preassembly.

In addition to the erection, insulation, and cladding, the subcontractor had to: 1) provide all the connection detailing, shop, and erection drawings; 2) fabricate the structural steel as designed by the designer for the prime contractor; and 3) supply and install all girders and rails for 18 overhead cranes.

Before the start of the subcontractor's work, the prime contractor was responsible for delivering the concrete foundations, complete with anchor bolts installed and expected to supply a 300 ton and a 200-ton crawler crane, plus an 80 ton all-terrain telescopic crane with qualified operators. In addition, the prime contractor was responsible for supplying 18 overhead cranes, as well as all site office trailers for the subcontractor (Figure 7.6). During the construction of the CS, three changes in the scope of work were issued as follows:

Figure 7-6. CS Construction.

1. Change Order # 1: The prime contractor modified the subcontractor scope of work by adding a temporary wall between Units 2 and 3. This temporary wall was meant to close the first half of the CS while the subcontractor would be working on Units 3 and 4. The value of this change order was CAD 1,200,000 dollars and increased the steel structure quantity by 250 metric tons and the quantity of insulation and cladding by 5,000 square meters. However, the temporary wall could not be executed due to the design issue and it was replaced by cables and tarps and did not incorporate any structural steel support. This wall executed in December but collapsed under the wind load.
2. Change Order # 2: Related to additional insurance requirements.
3. Change Order # 3: This change order changed the payment mechanism of the contract between parties. In addition, the subcontractor estimated that about 125,000 man-hours were required to finish the work (110,000 man-hours direct labor and 15,000 man-hours of supervision). It should be noted that these hours included all the losses of time that had occurred since the beginning of the

project and included provisions for winter conditions. This change order also modified the subcontractor's scope of work by adding reception bays, snow barriers, and the low roof that had to be completed at the same time as Unit 4. These new elements increased the steel structure quantity by 600 ton and the quantity of insulation and cladding by 6,000 square meters. The change order was drafted by the prime contractor according to the new milestones and man-hour estimates and was sent to the subcontractor on November 2014. However, the subcontractor was no longer willing to sign off on the estimated man-hours and milestones proposed by the prime contractor. Although this change order was revised for multiple times, parties could not come to an agreement. Finally, the subcontractor signed a revised change order, but this document did not represent the same milestone and man-hours required to complete the work. The subcontractor planned to finish up to Unit 3 of the ICS (Units 1, 2, and 3) by March 2015 and Unit 4 completion would depend upon further negotiation with the prime contractor. The subcontractor also considered completing CS with 201,000 hours (186,000 man-hours of direct labor and 15,000 supervision hours). The prime contractor never signed this change order.

7.2.3. Overview of Issues

During the execution of the proposed change (CS), project parties experienced several major issues. These issues can be classified into three major categories as follows:

- **Schedule impact:** As mentioned earlier the subcontractor's schedule had been modified several times due to the following reasons: differing site conditions, delay in foundation and site preparations, and delay in the delivery of the prime contractor equipment. Because of the issues the subcontractor could not progress at their planned rate before September 2014. The prime contractor confirmed that the delay in completion of foundations had an impact on the subcontractor start of work and progress in the early stages of work.
- **Operation impact:** The operation of the subcontractor was lower than expected. This situation generated delays in the erection of the structural steel and in the insulation and cladding activities. The loss of productivity was caused due to: 1) weather: downtime hours occurred due to snowstorm and icy rain as well as the hours the cranes were down because of wind above the regulated specifications;

2) equipment: hours lost because crane operators were not available as well as mechanical issues with equipment; 3) safety issues: hours lost when the site was shut down due to safety issue; 4) interference with other trade—hours lost because other trades were working in the same area and the subcontractor was unable to carry out their work; 5) groundwork: hours lost because the subcontractor had to perform groundwork around the cranes prior to executing the erection; 6) other: hours lost which are not classified in abovementioned categories. Figure 7.7 shows the proportion of downtime due to the above-mentioned reasons.

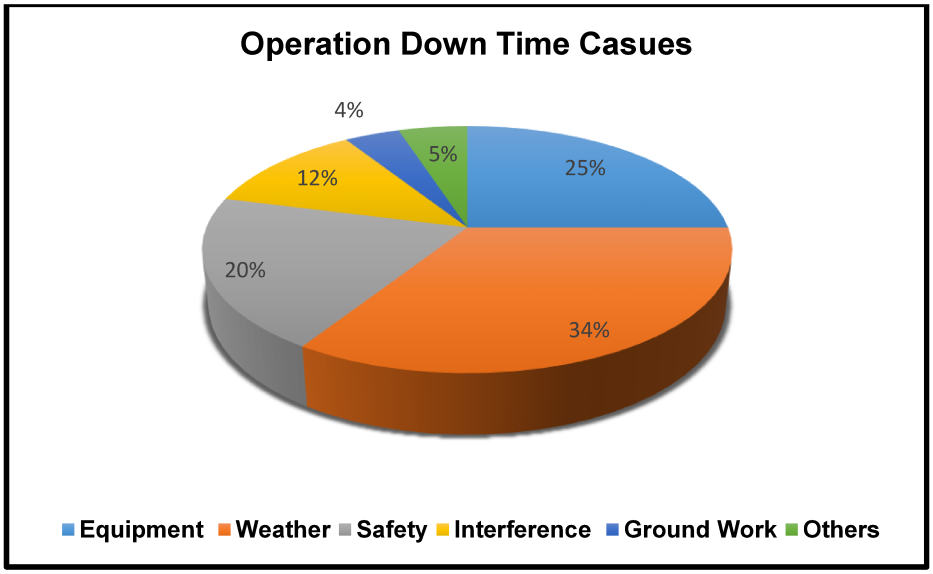


Figure 7-7. The Proportion of Downtime for Erection.

- **Financial Impact:** At the time of termination of the contract between involved parties, the subcontractor had executed around 51% of the work. Table 7.1 summarizes overrun of hours for the construction of CS. CPI was 23% based on the average cost of labor ($145).

Table 7-1. Time and Cost Overrun for the construction of the ICS.

	Hours	Cost
Planned Man-hours	44,522	$ 6,455,690
Earned Value at Termination	22,827	$ 3,309,915
Total Actual at Termination	97,827	$ 14,184,915
EAC	190,803	$ 27,666,394
Loss of Productivity	75,000	$ 10,875,000

- **HSE Impact:** At the time of termination, the subcontractor had experienced several serious safety incidents. Table 7.2 shows the cumulative numbers of different safety issues. One of the main reasons for safety issues can be linked to increased manpower. Newcomers must go through a period of learning during which they must familiarize themselves with the work.

Table 7-2. Health and Safety Performance Indicators.

Health and Safety Performance		No. at Termination
HSE Indicators	Number of First Aid Incidents	43
	Number of Medical Aids	3
	Number of Lost Time Injuries (LTI)	0
	Number of Modified Work Cases	35
	Number of Property Damage Incidents	57
	Number of Near-Miss Incidents	19

7.2.4 Applying Fuzzy Risk-based Change Management System

In this section, the developed model in Chapter 4 is applied using the above-mentioned case study. Although this case study contains a considerable amount of data in regard to delaying events, some important information related to certain key major issues was not available. Since retrieving information is a time-consuming process and the project had already been completed, some assumptions were made:

1. Change identification stage is not necessary because this change is already identified; and
2. It is assumed that there are no consequential changes.

The first step was to register the project information as well as information related to the identified change. The purpose of this step was to capture projects details used as historical data for future assessment. The project details should include enough information regarding the project scope of work. In addition, other essential information needed to be added to this module such as the planned start and finish date of the project, project manager information, and project schedule ID number.

The next step was to enter the information regarding the change. This module is a major component of the FRCM model and is designed to capture key information regarding the proposed change. First, any change needs to have an identification number, which is a primary key in the developed relational database. The next step was to select change type which is an elective change for execution purpose (Figure 7.8).

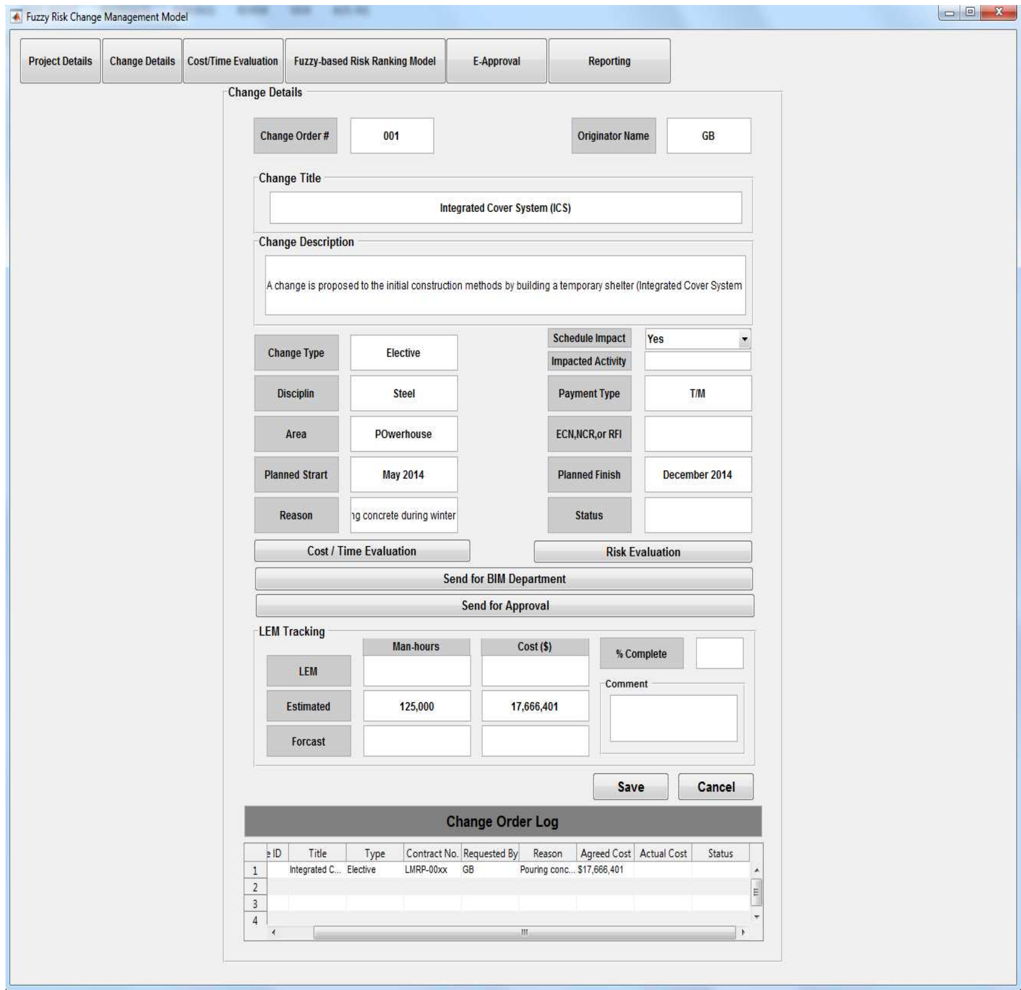


Figure 7-8. Change Details

The third step was the change assessment module which is designed for estimating resources, time, and cost associated with the proposed change. This step is explained in detail in Chapter 4 section 4.3.3. Table 7.3 is created based on the available actual information in the case study.

Table 7-3. CS Manhours and Cost.

		Hours			Cost		
No.	Indirect Cost	Sheet-metal Workers	Ironworkers	All	Sheet-metal Workers	Ironworkers	All
1	Mobilization	597	1194	1791	$ 74,642	$ 149,283	$ 223,925
2	Health & Safety	358	717	1075	$ 44,785	$ 89,570	$ 134,355
3	Quality Control	0	4777	4777	$ -	$ 310,510	$ 310,510
4	Superintend	2866	4013	6879	$ 415,605	$ 581,847	$ 997,452
5	Demobilization	239	239	478	$ 25,080	$ 25,080	$ 50,159
6	Direct Hours	40618	69382	110000	$5,889,628	$10,060,372	$15,950,000
7	**Total**	**44679**	**80321**	**125000**	**$6,449,739**	**$11,216,662**	**$17,666,401**

The next step was to develop the FRRM. After the above-mentioned steps were completed, the case study was analyzed through the second approach proposed for determining risk score. For this step, two experts in the risk domain were consulted for quantifying impact level and consequence probability for each impact as mentioned in Section 4.2.3.3, step 3. Figure 7.9 shows the sample of calculation sheet as demonstrate in MATLAB for the lowest level of hierarchy (Level 3).

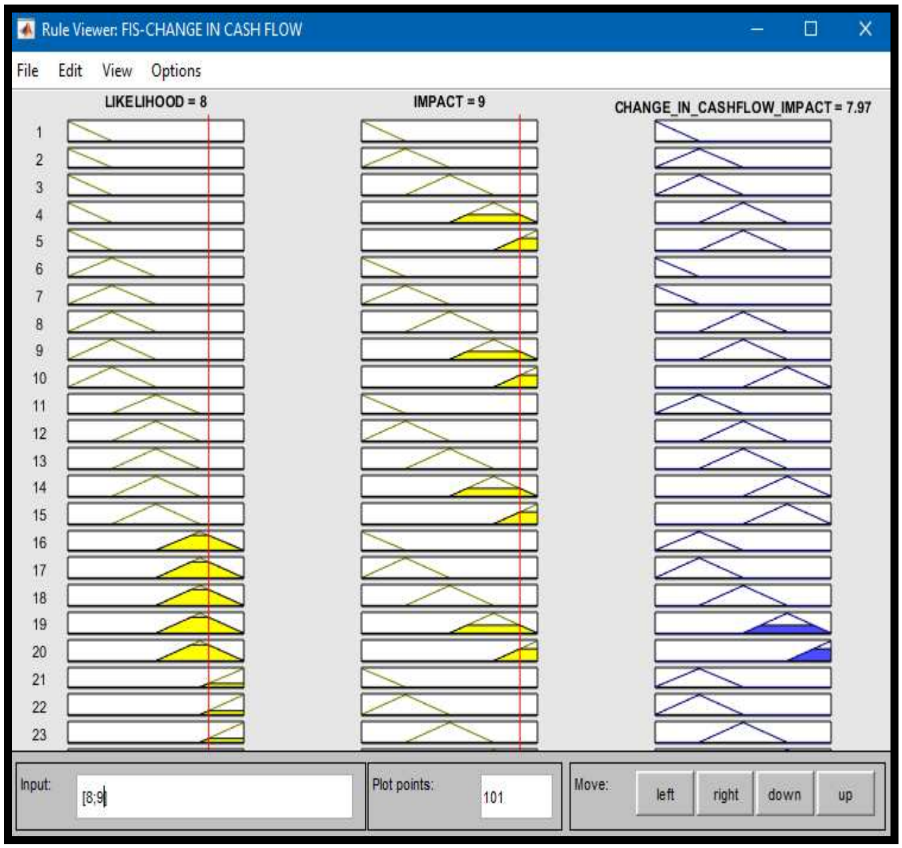


Figure 7-9. Sample of Lowest Level of Hierarchy Calculation

Table 7.4 shows the results of the likelihood and impact of the lowest level of the hierarchy. The experts identified the score for this change that may have an influence on the project without sharing with them the actual data.

Table 7-4. Score of Lowest Level of Hierarchy.

Level 3 ID	Likelihood	Impact	Score
Change in Cash flow	6.5	8	7.9
Increase Overhead	5	3	5.6
Direct Cost	7	8	8.4
Project Schedule	5	4	6.5
Rework and Demolition	5	4	5.5
Quality	2.5	2.5	2.5
Safety	3.5	4	5
Health	0	0	0
Environment	2	3	3

Once the value of consequence and probability were identified, these values were used as inputs for the interim level of the hierarchy. Figure 7.10 shows a sample calculation sheet as demonstrated in MATLAB for the interim level of hierarchy (Level 2). For each interim level criteria, three values were needed. For example, the value for cash flow deficiency, increase in overhead, and an increase in total project cost should be calculated from the previous level in order to calculate Financial Impact value.

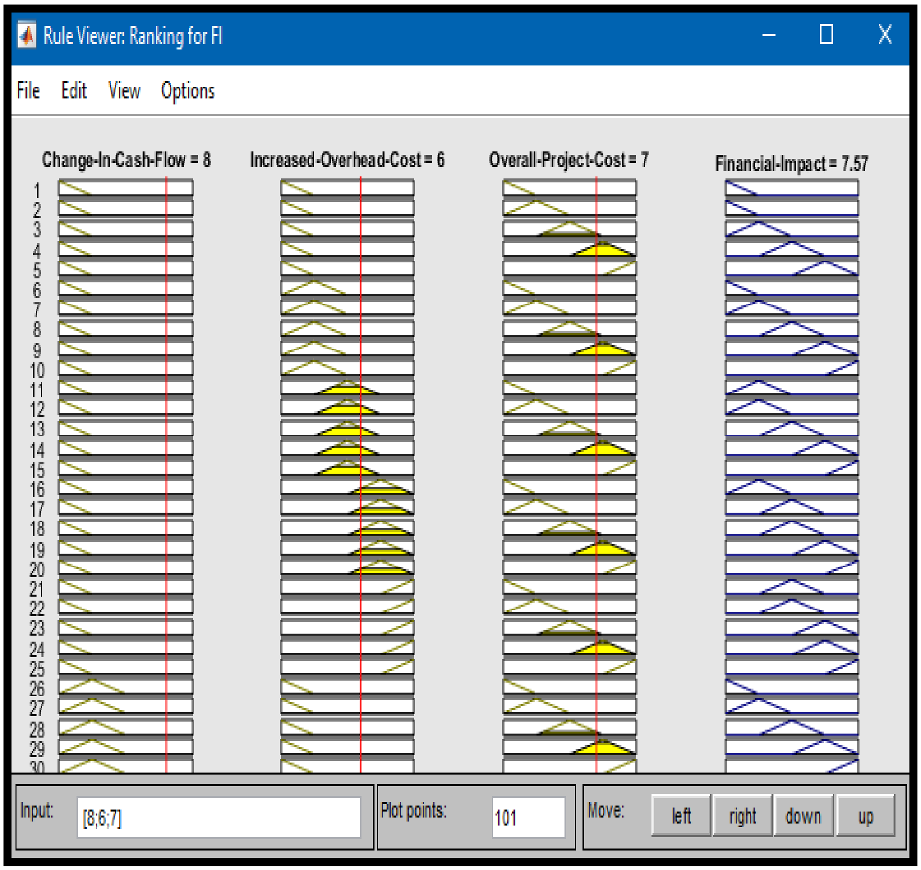


Figure 7-10. Sample of Interim Level of Hierarchy Calculation.

Table 7.5 shows the score for the interim level of the hierarchy. These values express the score of proposed change regarding Financial, Operational, and HSE aspect.

Table 7-5. The Score of Interim Level of Hierarchy.

Level 2 ID	Level 3 ID	Level 3 Score	Level 2 Score
Financial	Change in Cashflow	7.9	8
	Increase Overhead	5.6	
	Direct Cost	8.4	
Operational	Project Schedule	6.5	6.45
	Rework and Demolition	5.5	
	Quality	2.5	
HSE	Safety	5	5
	Health	0	
	Environment	3	

After the interim level score was calculated, the outputs of the interim level were mapped on the final FIS where the final FIS is defined in MATLAB, as shown in Figure 7.11 to calculate the total risk score of the proposed change, the final FIS only needed the values for the Financial, Operational, and HSE.

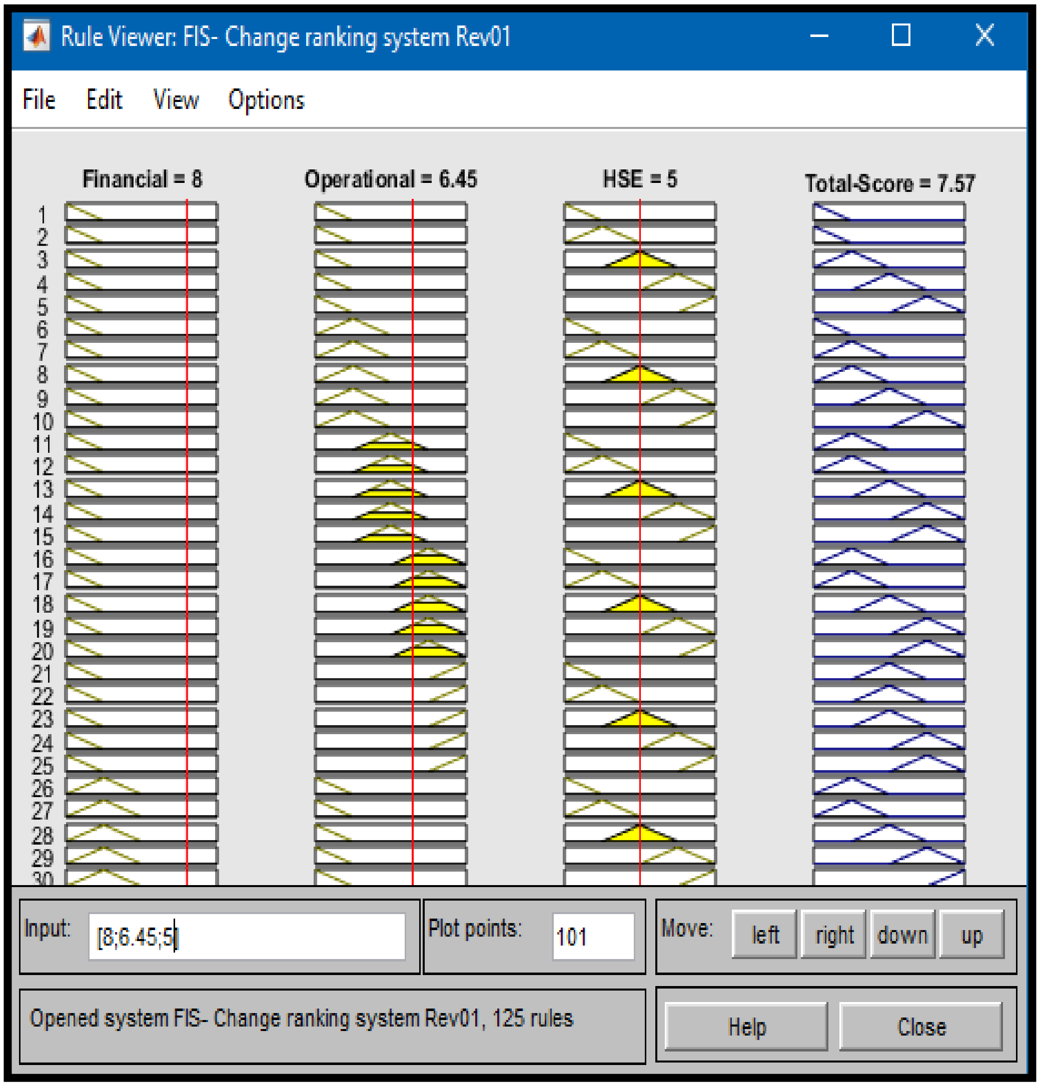


Figure 7-11. Total Risk Score.

The total risk score of the proposed change was calculated as shown in Figure 7.12. Financial, Operational, and HSE scores were 8, 6.45, and 5, respectively and the total score was 7.57. The above steps for calculating the total score is encapsulated in the FRRM, as shown in Figure 7.12. The result shows that CS is considered as a risky change. However, the risk associated with CS was not considered by the partners. As can be seen, the proposed model could be helpful in assessing the risk of change orders.

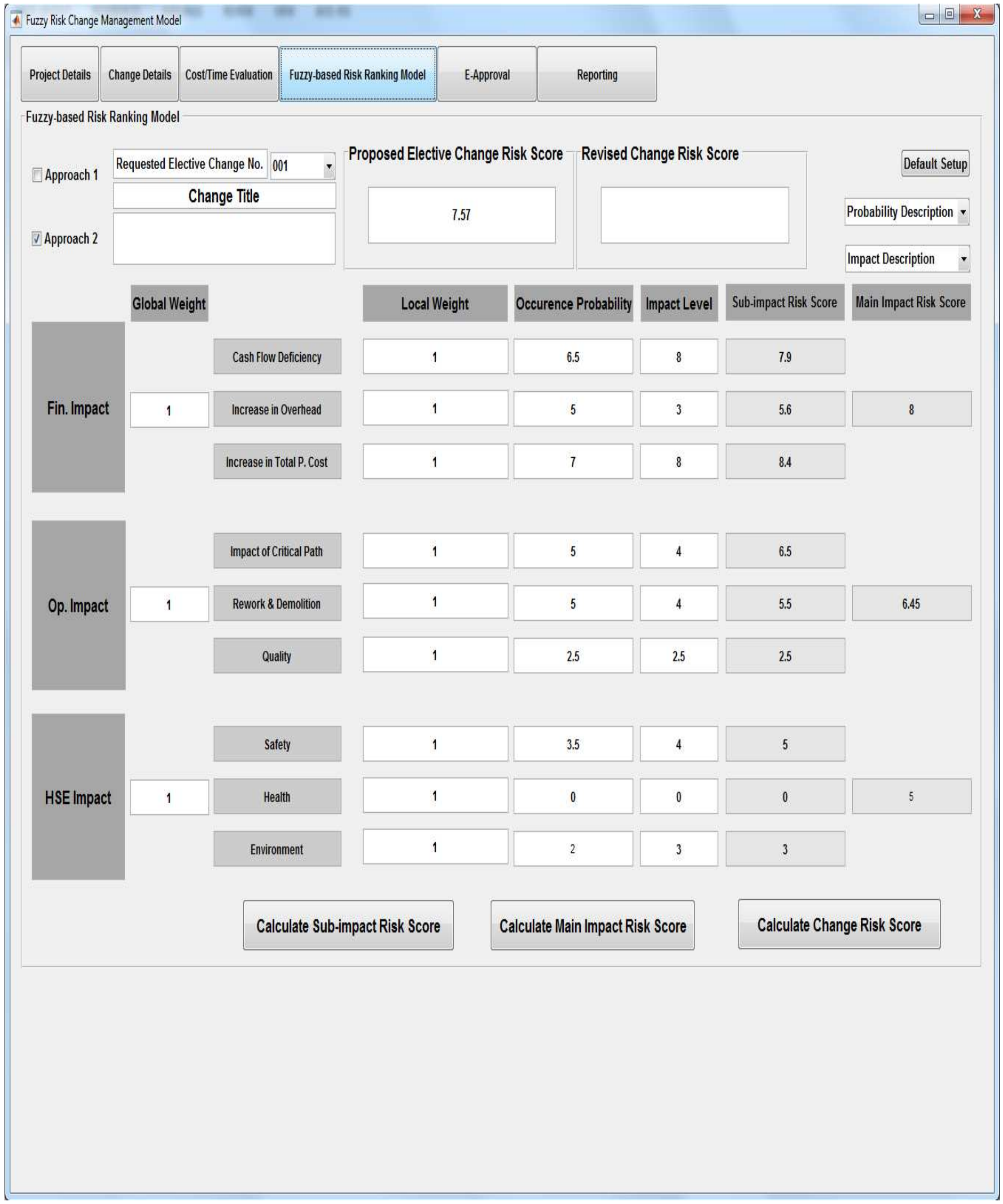


Figure 7-12. Result of the Fuzzy-based Risk Ranking.

7.3 Forecasting Labor Productivity Case Study

This section examines the validity of the developed PSO-RBFNN model using data collected from the concrete structure data to verify its applicability in predicting labor productivity for formwork. To gather the required data for validating the developed model's applicability, extensive data for input was collected from daily reports, progress reports, and daily weather reports. These documents were studied to extract weather-

related data (such as Wind Speed, Precipitation, Humidity, and Temperature), and work-related data (the data related to Work Type and Method). Work Type is related to the different types of structural members such as Slabs or Piers. The Work Method covers the different types of formwork used in this project. Formwork was divided into major techniques as follows: 1) built-in Place forms which are the traditional wooden forms; 2) climbing formwork (crane-climbing), which is the formwork displaced upwards with the help of crane; and 3) labor-related data, which is the data related to Gang Size in terms of number of persons. Labor percentage is the percentage of labor (helper) in a crew.
Project information is related to the number pours per area, shown in Table 7.6. A total of 783 data instances were collected for installation of formwork, as shown in Table 7.7. For each data collection instance, the above-mentioned data were documented. The dataset is divided into training and testing datasets based on 80 and 20 percentage. In other words, 626 data points for training dataset and 157 data points for testing dataset. The daily weather information, temperature, humidity, wind speed, and precipitation were gathered from the Environment and Climate Change Canada (ECCC) website. This historical data tool provides the option of acquiring precise data (ECCC, 2019). Table 7.8 shows the daily weather report gathered from ECCC. After gathering the data from the different resources, the data was compiled to a spreadsheet format as input for the developed PSO-RBFNN model in Chapter 5 (Table 7.9).

Table 7-6. Number of Pours per Area.

Area	**Number of Pour**
Centre Transition Dam	88
North Service Bay	34
North Transition Dam	29
Separation Wall	45
South Service Bay	140
South Transition Dam	326
Unit 1 - Intake	163
Unit 1 - Powerhouse	94
Unit 1 - Tailrace / Draft T Outlet	91
Unit 2 - Intake	163
Unit 2 - Powerhouse	93
Unit 2 - Tailrace / Draft T Outlet	94
Unit 3 - Intake	163
Unit 3 - Powerhouse	93
Unit 3 - Tailrace / Draft T Outlet	90
Unit 4 - Intake	173
Unit 4 - Powerhouse	109
Unit 4 - Tailrace / Draft T Outlet	94
Others	40
Grand Total	**2122**

Table 7-7. Sample of Installed Formwork Installed per Day.

Date	FW Qty.	Date	FW Qty.	Date	FW Qty.	Date	FW Qty.	Date	FW Qty.	Date	FW Qty.
14-Jun-14	6.232	3-Dec-14	276.23	5-May-15	305.26	28-Jun-15	97.73	18-Aug-15	65.66	14-Oct-15	97.52
10-Jul-14	2.856	5-Dec-14	159.06	7-May-15	159.06	29-Jun-15	243.9	20-Aug-15	71.51	15-Oct-15	71.09
19-Aug-14	122.75	8-Dec-14	148.81	8-May-15	116.7	30-Jun-15	383.21	22-Aug-15	285.63	16-Oct-15	295.6
21-Aug-14	80.48	10-Dec-14	73.1	9-May-15	315.81	1-Jul-15	464.985	23-Aug-15	142.53	17-Oct-15	183.33
24-Aug-14	159.47	13-Dec-14	73.08	10-May-15	122.03	2-Jul-15	463.88	25-Aug-15	93.52	18-Oct-15	54.94
9-Sep-14	159.47	15-Jan-15	159.06	11-May-15	145.21	3-Jul-15	184.75	26-Aug-15	59.58	19-Oct-15	121.22
11-Sep-14	112.176	18-Jan-15	160.91	12-May-15	146.2	4-Jul-15	479.8	27-Aug-15	189.05	20-Oct-15	85.34
12-Sep-14	168.69	21-Jan-15	148.37	13-May-15	159.06	5-Jul-15	84.84	28-Aug-15	191.64	21-Oct-15	241.49
16-Sep-14	57.12	22-Jan-15	160.91	14-May-15	305.26	6-Jul-15	214.39	29-Aug-15	413.412	22-Oct-15	154.48
17-Sep-14	42.78	31-Jan-15	159.06	17-May-15	157.81	8-Jul-15	543.44	30-Aug-15	302.28	25-Oct-15	74.97
23-Sep-14	82.46	3-Feb-15	133.34	18-May-15	146.2	9-Jul-15	271.79	31-Aug-15	370.78	26-Oct-15	449.67
24-Sep-14	138.27	9-Feb-15	150.44	19-May-15	249.575	10-Jul-15	209.34	1-Sep-15	506.76	27-Oct-15	165.96
26-Sep-14	13.195	10-Feb-15	159.06	20-May-15	110.51	11-Jul-15	395.9	2-Sep-15	133.85	28-Oct-15	109.62
28-Sep-14	54.264	14-Feb-15	157.81	21-May-15	135.46	12-Jul-15	240.33	3-Sep-15	406.22	29-Oct-15	225.93
3-Oct-14	56.03	23-Feb-15	159.06	22-May-15	354.46	13-Jul-15	207.2	4-Sep-15	194.19	30-Oct-15	175.5
5-Oct-14	138.27	26-Feb-15	97.68	24-May-15	353.87	14-Jul-15	117.68	5-Sep-15	44.96	31-Oct-15	362.45

Table 7-8. Daily Weather Report.

Date	Temp (°C)	Humidity	Total Precipitation (mm)	Wind Speed(km/h)
1/1/2014	-35.4	67%	0	<31
1/2/2014	-36.1	65%	0	39
1/3/2014	-33.4	67%	0	48
1/4/2014	-26.7	73%	4.8	61
1/5/2014	-23.8	84%	0	<31
1/6/2014	-18.3	85%	0	61
1/7/2014	-16.5	80%	0	57
1/8/2014	-24.2	69%	0	69
1/9/2014	-25.4	69%	0	48
1/10/2014	-17.1	76%	0	37
1/11/2014	-9.7	86%	0	39
1/12/2014	-8.7	90%	0	46
1/13/2014	-6.5	88%	0	39
1/14/2014	-3.3	93%	0	37
1/15/2014	-10.4	85%	0	41
1/16/2014	-19.7	84%	0	<31
1/17/2014	-20.1	86%	0	<31
1/18/2014	-14.5	90%	0	<31
1/19/2014	-17.3	90%	0	39
1/20/2014	-16.7	88%	0	41
1/21/2014	-19.5	80%	0.5	52
1/22/2014	-20.6	78%	0	37
1/23/2014	-27.2	75%	0	41
1/24/2014	-30.4	75%	0	<31
1/25/2014	-24.6	80%	0	32
1/26/2014	-14.3	89%	0	

Table 7-9. Sample of Prepared Data Sheet for PSO-RBFNN Developed Software.

T	H	P	WS	GS	LP	WT	FL	WM
20	50	0	8	20	30	1	14	1
11	44	0	13.4	15	33	2	11	1
11	94	1	37	8	38	1	12	2
13	70	0	18	12	33	1	10	2
14	38	0	18	19	32	1	12	1
6	75	0	18	22	37	1	16	2
-6.5	56	0	10.5	21	33	2	7	1
-9	76	0	18	11	37	1	14	2
-12	81	0	31	11	37	1	14	2
-4.5	48	0	14.1	19	33	1	7	2
-0.5	53	0	7.5	22	36	2	5	1
21	61	0	18	18	33	2	16	1
23	86	0	11	23	35	2	12	1
2	63	0	23	9	33	2	16	1
15	67	0	14	19	37	2	15	1
21	63	0	16	20	30	1	12	2
21	75	0	8	21	33	1	15	2
7	65	1	31	11	37	1	10	2
-4.5	48	0	14.1	20	30	2	7	1
5	72	0	21	8	37	2	16	1
-5	90	3	26	11	37	1	13	2
-1	93	1	14	11	37	1	13	2
-7	41	0	7.9	20	30	1	8	2
-3	90	3	39	9	33	2	13	1

After implementing the data preprocessing steps discussed earlier, the input data was prepared to be fed to the model. For the PSO model, the swarm population size was set to 50, with each particle in the algorithm representing variables of c_i, σ_i, and w_{ij}. The input data space span was limited to 0 to 1 and RBF center c_i constrained in the range of [0, 1]. Also, the width σ_i was considered in the range of [1, 50] and the connection weights w_{ij} constrained in the range of [0, 100]. Therefore, given the defined range of parameters, the particle swarm was initialized randomly. The maximum iteration number was defined as 100 iterations and MSE less than or equal to 0.0001 was defined as the stop criterion. To evaluate the performance of the proposed PSO-RBFNN, the prediction error was evaluated against the actual prediction. Thereby, historical data were divided into two groups with most of the data residing in the proposed model training set and the remaining in the testing set. As mentioned in the previous sections, this research utilized MSE as an error predictor. Table 7.10 shows the performance evaluation results of the proposed model.

Table 7-10. Performance evaluation results of the PSO-RBFNN model.

Performance Indicators	Value
R^2 Train	0.8514
R^2 Test	0.8354
MSE Train	0.0196
MSE Test	0.02003
RMSE Train	0.140
RMSE Test	0.144
MAE Train	0.094
MAE Test	0.107

Next, the trained model was validated against the actual data of the case study. The predicted BP, which was used in the calculations by the project team, was considered as 25 hrs./m^2. Using the proposed model, productivity was predicted as 26.7 hrs./m^2 for the same job. Therefore, the model performed better in predicting BP and may improve calculation accuracy. Table 7.11 presents the comparative predicted productivity by the project team and the proposed model. It should be noted that 25 hrs./m^2 is used during execution phase of the project.

Table 7-11. Comparative predicted productivity.

	Productivity (hrs./m^2)	Error%
Baseline Productivity	25	-
Proposed model	26.7	6.8%

7.4 Loss of Productivity Quantification Case Study

After validating the BP and change order assessment, the developed SD model in Chapter 6 was employed for quantifying the effect of change orders on labor productivity. In addition to change order impact, the developed model defined and quantified the impacts of other influencing factors on labor productivity, namely as temperature and humidity, learning curve, overtime, crowding, and management disruption. ICS information was analyzed using the developed model to quantitatively measure the impact of the change order in the project on labor productivity. The project was analyzed using the developed SD model, as well as Leonard and Ibbs models. The results obtained from the three models were compared and the conclusions extracted.

7.4.1 Quantifying Loss of Productivity Using Ibbs and Leonard Models

The ICS change orders man-hours value were 125,000 hours, which increased the scope of work by 10.5% due to the modification to the construction methods. Ibbs and Leonard models were employed in this section to analyze the impact of CS change order on labor productivity. Referring to Figure 7.13, change order percentage was plotted to Leonard's graphical models and the productivity value loss was ~12%.

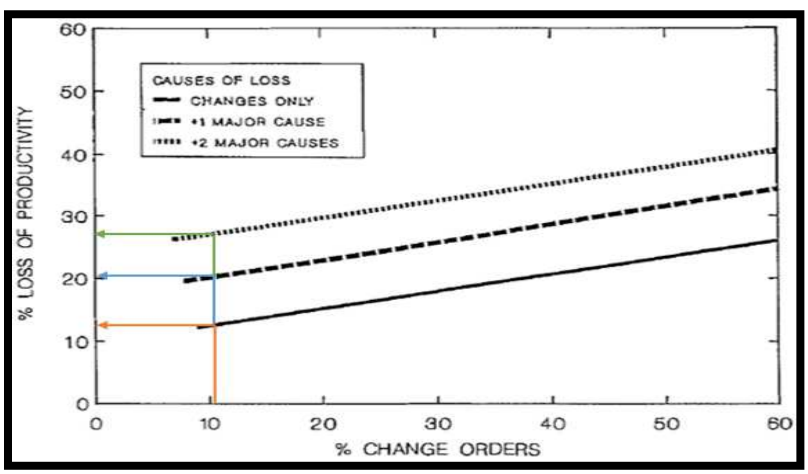


Figure 7-13. Quantifying Loss of Productivity Using Leonard's Model.

It was assumed that there was a major contributing factor to the loss of productivity, overtime impact, along with the CS change order due to employing the available manpower on extended overtime. Thus, loss of productivity was 21%, as shown in Figure 7.13. In addition, the existence of two major contributing factors was assumed such as overtime and temperature and humidity, and loss of productivity was around 28%. As can be seen from Figure 7.14, three options were available for quantifying the loss of productivity, normal early, and late curves. The late curve shows a 20% loss of productivity. The normal curve shows a 10% loss of productivity and early changes shows a 3% loss of productivity.

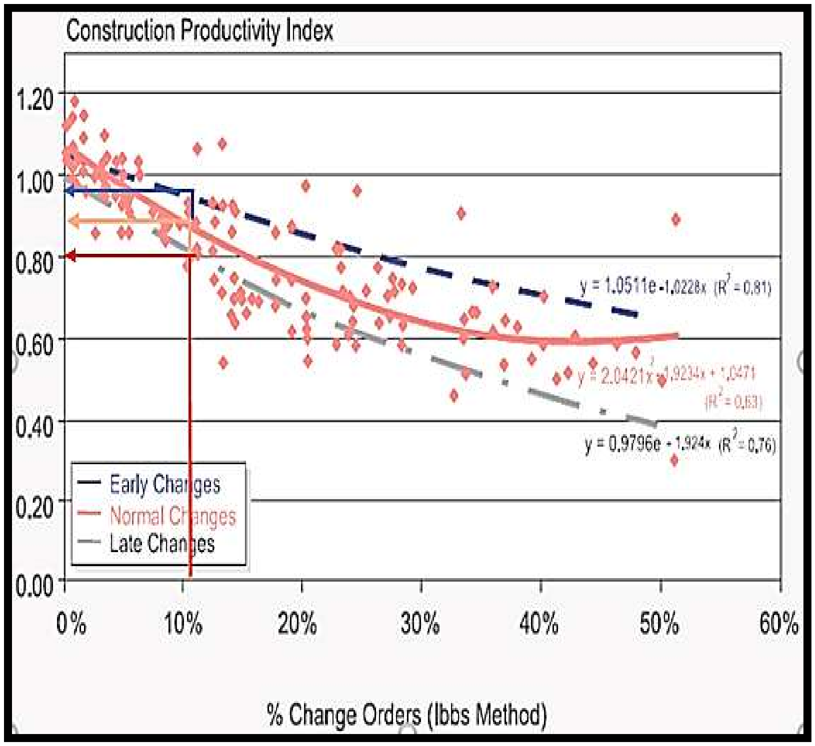


Figure 7-14. Quantifying Loss of Productivity Using Leonard's Model.

It should be noted Ibbs' model does not consider the effect of other contributing factors in the loss of productivity quantification. Table 7.12 summarize the loss of productivity quantification using Leonard and Ibbs models. Furthermore, Leonard and Ibbs models cannot apportion loss of productivity to other major contributing factors to loss of productivity. Using Ibbs and Leonard models requires an experienced user in order to utilize the right curve. As such, these models should be used as a last option.

Table 7-12. Quantifying Loss of Productivity Using Ibbs and Leonard Models.

	Leonard			**Ibbs**		
	Change	Change +1	Change +2	Late	Normal	Early
Loss of Productivity	12%	21%	28%	20%	10%	3%
Planned Man-hours	178,285 hrs.					
Loss Hours	21,394	37,439	49,919	35,657	17,828	5,348
Percentage of Error	20%	40%	87%	33%	33%	80%
Actual Man-hours	205,022 hrs.					
Actual Loss of Productivity	15%					
Actual – Planned Man-hours	26737 hrs.					

7.4.2 Quantifying Loss of Productivity Using Measured Mile Analysis

To do a comprehensive analysis of project documents, which are not easily available all the time, the MMA is required. Contractor's progress and productivity analysis reports were reviewed and analyzed for impacted and unimpacted productivity, as shown in Figure 7.15.

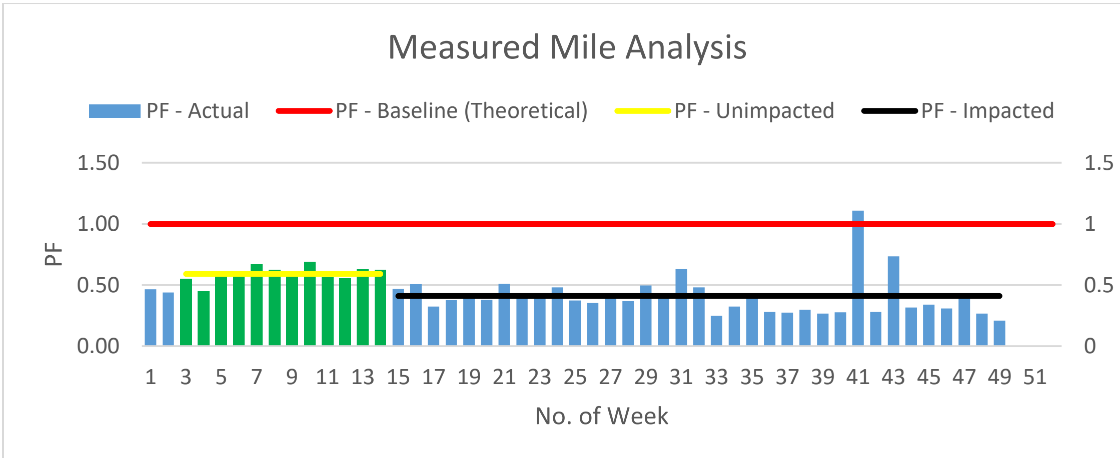


Figure 7-15. Quantifying Loss of Productivity Using MMA.

As shown in Figure 7.15, the distance between the yellow line and the black line represents the loss of productivity due to change order. Based on the unimpacted period, it can be seen that the contractor's best performance on site was 59% of BP for the unimpacted period. This value is the MMV, as well as the value used to compare the SD model result against it. Impacted productivity was 0.41 of BP. Thus, loss of productivity was 18% (59%-41%). The percentage of error is equal to 20% (18%-15%)/15%.

7.4.3 Quantifying Loss of Productivity Using Developed SD Model

Figure 7.15 presents clearly that contractor's laborers were working inefficiently even prior to the issuance of a change order. Using the developed SD model, the reason behind this inefficiency can be explained by calculating the expected labor productivity on site after factors that might affect labor productivity such as temperature and humidity, crowding, change order, and learning curve effects were introduced (Figure 7.16).

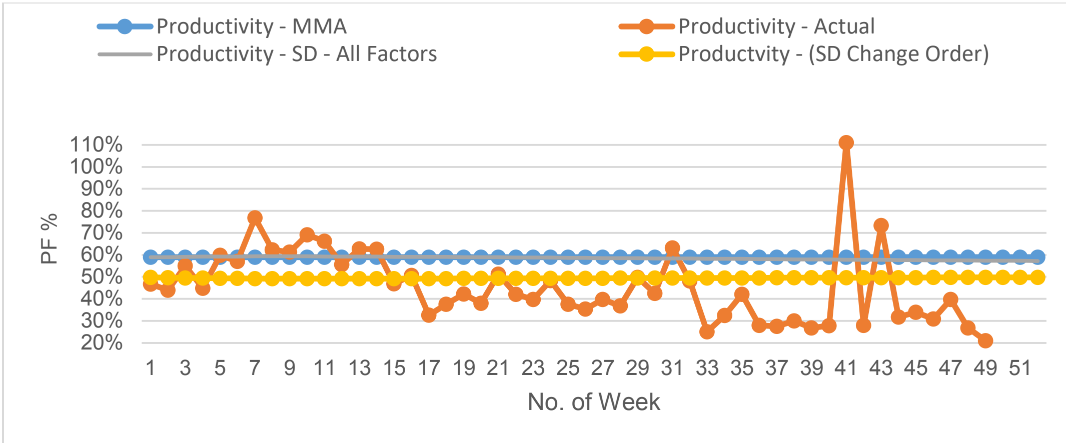


Figure 7-16. Time (Week) vs. Productivity.

The analysis shows an average loss of productivity of 16.4% due to crowding, learning curve, temperature and humidity, as well as a change order. The average loss of productivity was equal to 8.4% (2.1 hrs. $/m^2$) and the difference should be apportioned to the other contributing factors. As more new resources were assigned to the project, labor productivity was impacted by 3.7% (0.925 hrs. $/m^2$) due to learning curve. Less than 2% (0.5 hrs. $/m^2$) of loss in productivity was attributed to temperature and humidity, as well as 2.8% (0.7 hrs. $/m^2$) to crowding as more resources were assigned to the project (Figure 7.17).

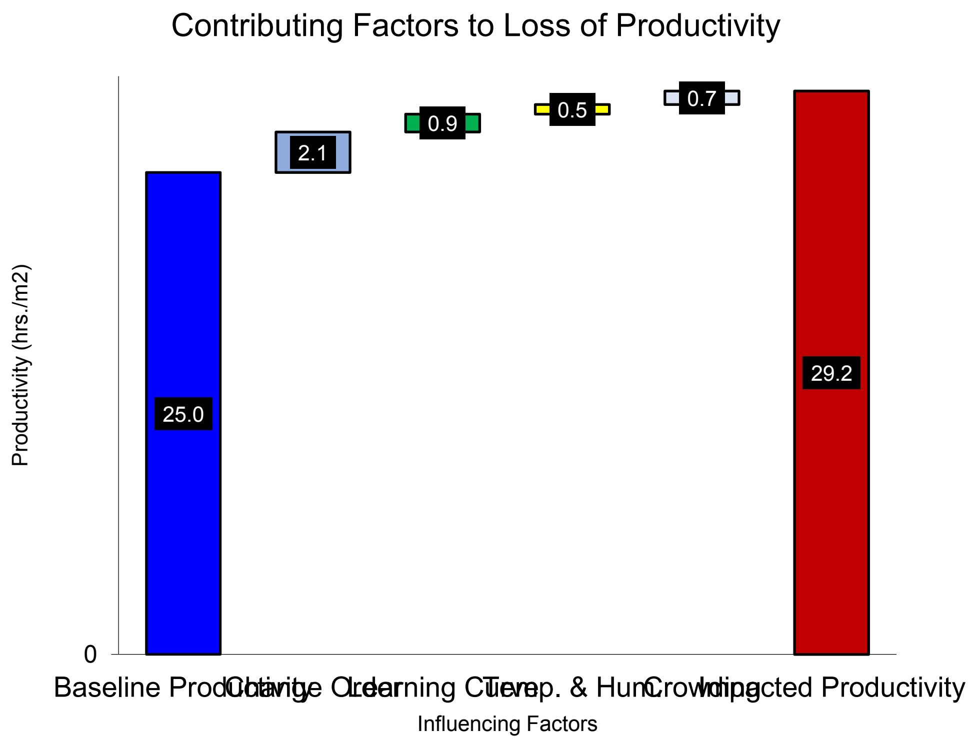


Figure 7-17. Value of Contributing Factors to Loss of Productivity.

7.4.4 Comparison of Different Techniques in Quantifying Loss of Productivity

The four techniques explained above are compared and discussed in this section. Table 7.13 and Figure 7.18 summarize the previous techniques.

Table 7-13. Summary of Previous Techniques.

	Actual	Leonard	Ibbs	MMA	SD
LOP	15%	12%-28%	3%-20%	18%	16.4%
% Error		20%-87%	33%-80%	20%	9.3%

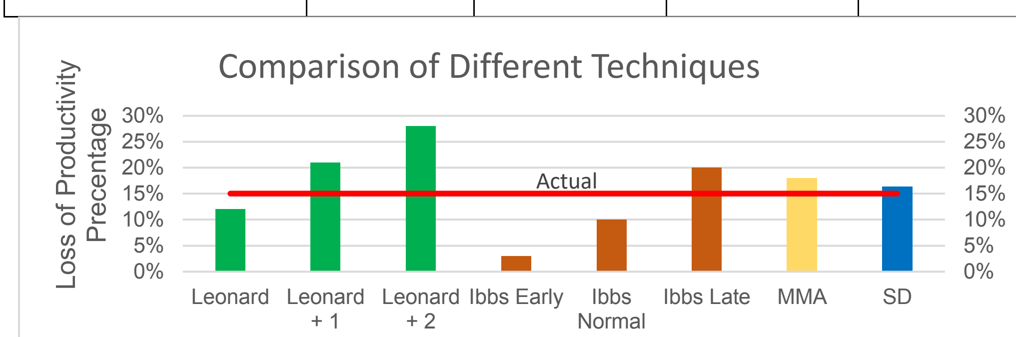


Figure 7-18. Comparison of Different Techniques Results

As can be seen from Table 7.13 and Figure 7.18, the SD model is capable of producing more accurate results in comparison to the other techniques. In addition, the SD model can allocate loss of productivity to all contributing factors. Using Leonard and Ibbs models can lead to over- or under-estimating the value of productivity loss. Leonard's model is not applicable for change orders at less than 10%. In addition, Leonard's model takes into consideration the impact of a change order along with two other contributing factors in lump sum number. Ibbs model takes into consideration the effect of a change order as well as the timing of change order. However, Ibbs model does not take into consideration the effect of other contributing factors.

7.5 Summary

This chapter presented the developed framework application for quantifying the loss of productivity due to a change order using a real-world case study of a massive concrete structure in Canada. To validate the applicability of the developed models and their accuracy, the FRRM was used in the change management section to see its applicability in highlighting the benefit of encouraging positive changes and discourage negative changes. In the second validation process, the PSO-RBFNN was used to predict and estimate labor productivity, which can be used as a baseline value for the SD model of the last component. Finally, the SD model was used to quantify the loss in productivity due to change orders and other contributing factors such as crowding, learning curve effect, and Temperature and Humidity. The validation of the developed framework major components was conducted successfully at all three stages and the result shows that the proposed framework solidly accomplished all its intended purposes, ranking change orders, predicted productivity, and quantifying the loss of productivity. It should be noted that the current developed system must be utilized as a supplementary tool, not as a comprehensive substitution for a qualified expert.

8. CHAPTER EIGHT: SUMMARY and CONCLUSIONS

8.1 Summary and Conclusions

Current change management systems are not comprehensive and practical enough for quantifying the real impact of change orders and other managerial decisions including overtime, acceleration, and new hires on labor productivity. Although in most cases, contractors and clients recognize the impact of changes on productivity, they neglect the ripple effect a change order will have on a project because it is not tangible during change order assessment. This study proposed a change management framework for quantifying labor productivity loss due to change orders and managerial policies throughout all phases of construction projects. The proposed framework consists of three major models: (1) FRCM, (2) AI-based model, and (3) SD model.

The FRCM was developed to accept or decline the requested change orders except mandatory ones considering their impact on the project and consequential changes that they might result in. FRCM includes several main modules. The main module includes a Fuzzy Risk Ranking System (FRRS) to prioritize change orders. In this stage, (F-AHP was utilized to calculate the relative importance weight to be used in prioritizing requested change orders. By estimating the impact level of each requested change, only changes with acceptable impacts would be confirmed and performed. In addition, a BIM model was adopted and modified to capture the consequential changes that may arise from initial change(s). This consisted of four main steps: (1) 3D project model development (baseline model), (2) modified 3D model development including the primary requested changes, (3) comparison of baseline and modified model, and (4) report generation based on the comparison to group the changes.

A novel AI-based model (PSO-RBFNN) was developed to calculate BP considering environmental and operational variables. The estimated BP was used as the initial value for the next developed model, the SD model. AI was applied to overcome some SD limitations including mathematical complexity, difficulties in identifying the relationship among variables, and inability in considering variables at the operational level. Thus, only strategic level variables, including change orders and managerial policies, were considered in SD modeling.

Finally, a novel SD model was developed to quantify the impact of change orders and different managerial decisions in response to imposed change orders on the expected productivity during the lifecycle of a project. The developed SD model was calibrated and validated using a real case study of a massive concrete structure data and acceptable results were obtained. The developed framework was validated through several case studies and the results show that the various consequences derived from a change in combination with the major environmental and operational variables of the project were identified and analyzed successfully. The proposed framework could help the project team identify and quantify the cumulative impact of change orders on labor productivity (productivity loss) in a timely manner and facilitate the decision-making process. The final SD model, which was fed by the other developed models, could provide decision-makers with an opportunity to explore possible cost-effective intervention policies and examine a number of scenarios.

8.2 Research Contribution

The contributions of this research are:

1. Development of an FRCMS as a tool that can aid in facilitating the decision-making process for proposed changes and encourages the integration of positive changes and reduces unnecessary changes and negative impacts on all project aspects as much as possible. The novel combination of FRR and BIM, alongside other modules (Change Identification, Change Registry, Final Approval, Change Implementation, and Change Closure), make the developed model a comprehensive change management platform for decision-makers. Two databases were designed to store project and change data along with entity relationships diagrams. These databases provide a data-sharing environment for managing changes at various stages of a project. Software was developed to incorporate the above-mentioned modules and other features necessary for efficient and effective change management during the course of a project as well.
2. The development of a novel AI-based model for estimating BP. First, the AI-based model can improve baseline labor productivity prediction accuracy and shows reliable performance from the point of generalization due to having the training and testing errors close to each other. BP helps to quantify the precise value of the loss of productivity due to the owner caused changes. The model predicts the best possible productivity that can be achieved by a contractor, which is BP. Second, it also improves SD modeling computation

capacity by reducing the need to establish the number of mathematical equations indicating the relationships among variables, making the SD model smaller, less complex, and more comprehensible to construction practitioners.

3. The development and implementation of an automated SD model to demonstrate the consequences caused by change orders in combination with the managerial policies along with some environmental and operational factors. The SD model is able to accurately assess the ripple effect of changes on construction labor productivity during the course of the project, while taking into account multifaceted managerial policies as well as environmental and operational influential variables. The developed SD model takes into account the man-hours and quantity installed. The productivity shows fluctuation due to different quality values as well as learning curve. Thus, including installed quantity in the analysis allows for quality and learning curve to be applied to the loss of productivity quantification. The developed model can take into account the non-linear behavior of construction projects. In other words, the developed model takes into account non-linear relationships between different factors affecting labor productivity are taken into consideration while developing the quantitative model.

8.3 Limitations

The limitations of the developed research framework are as follows:

1. For FRCMS, proactive change identification is hard to automate, as it requires considerable effort to reach an intelligent proactive system. So the developed FRCMS model is a reactive change management model that scrutinizes and ranks requested elective changes based on their impact risk score;
2. Interdependencies among criteria are not considered in developing Fuzzy Risk Ranking System;
3. The developed AI model was trained and tested on datasets of two high-rise buildings related to formwork operation. Thus, other datasets related to other activities are required to generalize the model for a construction project;

4. The developed SD model, it was constructed based on limited number of unstructured interviews. More interviews are needed to improve and expand the SD model and enhance its structure.
5. The developed SD model was tested and validated using one case study. Further validation is needed to measure its performance on other case studies; and
6. More variables should be studied and included in developing the SD to analyze its impact on loss of productivity.

8.4 Future Work

The following are some recommendations for future work:

1. Developing a proactive change management system;
2. Generating datasets related to other operations except formwork installation to perform an analysis to determine the underlying factors affecting labor productivity and quantify the loss of productivity in building construction;
3. Validating SD model using more case studies to indicate its performance; and
4. Performing more interviews to obtain additional experts' knowledge to improve and expand the SD model and enhance its structure.

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